



**DETERMINING AIR BASE INSTALLATION CAPACITY THROUGH
MULTIVARIATE ANALYSIS**

THESIS

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AFIT-ENV-16-M-139

**DEPARTMENT OF THE AIR FORCE
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Perry L. Cansick, BS

Captain, USAF

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Abstract

Per the Air Force Strategic Master Plan, the Air Force will adjust their current basing structure to provide the most effective and efficient installations to support national defense objectives. The Air Force may be required to make strategic basing decisions that close installations and relocate missions to achieve an optimal basing structure. However, before making these decisions, the Air Force needs to have a comprehensive understanding of installation capacity. This research offers an in-depth analysis of capacity for the benefit of Air Force planners responsible for making or informing strategic basing decisions.

This research provides an operational definition of installation capacity, which is necessary for measuring installation-level, infrastructure capacity. Using this definition, the research evaluates a set of capacity indicators using principal component analysis (PCA) and exploratory factor analysis (EFA). The results identify the underlying structure of the capacity data and determine what factors influence capacity. In addition, the component and factor scores provide information about capacity characteristics at each installation, and how they compare to other installations. Finally, this research created a composite scoring model, the Installation Composite Capacity (ICC), which measures the overall capacity at each installation. The Air Force can use the results and insight gained from this research to develop an optimized basing structure that meets present, and future, defense needs.

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Perry L. Cansick

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I. Introduction

A critical element of force presentation and power projection is how the Air Force uses current basing and logistics constructs and an awareness of areas needing improvement. As we change our way of delivering support services, our footprint will be adjusted to match. To preserve expeditionary capabilities and in support of readiness, we will continue to develop an affordable, deliberate approach to installations and provide a framework driven primarily by strategic direction rather than current fiscally driven exigencies.

–Strategic Posture Annex to the USAF Strategic Master Plan, May 2015

General Issue

The Air Force operates in a dynamic environment where enemies continuously pose new and unconventional threats to the United States. To ensure success and prepare for the future, the Air Force must advance faster than its opposition and remain on the cutting edge, despite facing several difficult challenges: operating at sequestered funding levels, replenishing and sustaining the oldest fleet of aircraft in the service's history, and maintaining the aging infrastructure that serves as the platform for its weapons systems. However, the Air Force will conquer these challenges through expert management of its systems and inventories, to include its installations and infrastructure. The Strategic Posture Annex to the Strategic Master Plan (SMP) highlights the need for a well-designed basing structure combined with an effective and efficient infrastructure management system to properly organize, train, and equip its forces. The Air Force will need the "right installations" at the "right place" to best accomplish its objectives (Department of the Air Force, 2015). In addition, the amount of excess infrastructure capacity continues to increase as the strength of the force decreases to the smallest since its inception (James, 2015). To align itself with the SMP and reduce excess capacity to

an optimal level, the Air Force will be required to make major basing decisions in the future.

The Department of Defense (DOD) can utilize two different methods to perform major realignment and closure actions. Per Section 2687 in Title 10 of the United States Code (10 U.S.C. 2687), the DOD and its service departments must follow certain procedures and reporting instructions before executing closure actions at installations. The service department becomes subject to 10 U.S.C. 2687 if the basing action exceeds one of three specified thresholds: a base closure with 300 or more civilian employees, a realignment that reduces the workforce by more than 1,000 employees, or a realignment that reduces more than 50% of the workforce (United States General Accounting Office, 2013). 10 U.S.C. 2687 requires the DOD to notify Congress of its proposed actions if any of the installations involved exceed the employment thresholds mentioned above. In its notification, the department must include a thorough evaluation of the actions and consider the criteria listed in 10 U.S.C. 2687, which is described in further detail in Chapter II (10 U.S.C. 2687). However, due to the lack of success in executing major basing action under 10 U.S.C. 2687, the DOD has traditionally performed closure and realignment actions via the second method: Congressional authorization of the Base Realignment and Closure (BRAC) process (United States General Accounting Office, 2013).

When Congress authorizes a BRAC, the DOD has the opportunity to provide recommendations to a commission as to which contiguous United States (CONUS) installations to close and what units to reorganize or relocate to more effectively use the space available. Five rounds of BRAC have occurred in DOD history: 1988, 1991, 1993,

1995, and 2005. In 1990, the DOD established evaluation criteria for selecting which bases it would recommend for closure (Lockwood & Siehl, 2004). The department used these same criteria in the four most recent BRAC rounds and focused on the “military value” of an installation (United States Government Accountability Office, 2012). Military value measures the usefulness of an installation and its ability to support different military missions (Department of the Air Force, 2005). In the 2005 BRAC, Congress directed the service departments to focus primarily on the military value criteria, which place considerable weight on infrastructure capacity concepts (United States Government Accountability Office, 2012). The military decision makers’ ability to find optimal basing solutions depended on the degree to which they understood installation capacity. If the DOD wishes to reduce excess capacity in the future, it needs a comprehensive understanding of installation capacity in order to determine an optimal solution.

As part of the 2016 Defense Authorization Bill, the Federal Government is requiring the DOD to submit infrastructure assessments and infrastructure inventories, to include a discussion of infrastructure capacity (Congress, 2016). Currently, Air Force installations are well positioned to submit these assessments and inventories through their sustainment management systems (SMS), but the installations do not have an SMS to specifically track infrastructure capacity. Without this capacity database, the Air Force and the DOD attempted to calculate installation capacity in previous BRAC rounds.

The first BRAC commission grouped installations into 22 different categories and assessed excess capacity for each category (United States Government Accountability Office, 2013). For the 1991, 1993, and 1995 BRACs, the DOD assessed the excess

capacity at each installation to select which bases to recommend for closure. In 2005, the DOD used a different method to evaluate capacity. The 2005 commission categorized installations by their primary mission and calculated a capacity-to-force structure ratio. For example, one ratio compared the number of personnel in a service branch to the total square footage of administrative space. The commission then computed the same ratio for 1989 and compared the two ratios to determine the amount of excess capacity. This method contains two major limitations: the capacities of individual installations were not calculated and the 1989 baseline assumes that installations were appropriately sized in that year (United States Government Accountability Office, 2013). However, this method gave decision makers and analysts a parametric estimate to help identify where or how much potential excess capacity exists. The Air Force used a similar method to estimate excess capacity in BRAC 2005.

The Air Force considered installation capacity during BRAC 2005 but never formally defined the term. In the Air Force's BRAC 2005 report, excess capacity was calculated by comparing the current inventory and the actual requirement via a ratio. Air Force analysts calculated capacity ratios for the airfield space, as well as facility space (Department of the Air Force, 2005). The report identified the first step in the Air Force's installation analysis as estimating the theoretical capacity of its installation. Each Air Force Major Command (MAJCOM) submitted capacities for their installations, but the results were not published in the report. The report does not identify what factors commands considered or whether there was any consistency between commands. However, the Air Force calculated Mission Capability Index (MCI) for each base by using an explicit model, executed by a group formed specifically for this purpose. The

Air Force developed and utilized MCI because Congress designated military value as the primarily means of evaluation in BRAC matters. This index attempted to quantify the military value of each installation and included several measures that related to infrastructure capacity. Bases received individual MCI scores for eight different mission areas, based on four criteria: current and future mission, condition of infrastructure, contingency and mobilization, and cost of operations and manpower (Department of the Air Force, 2005). Although MCI included installation capacity indicators, the term has yet to be defined. Without an operational definition of the term, the Air Force will not be able to explicitly measure installation capacity.

Research Rationale

Air Force planners must place serious consideration on installation capacity when making strategic basing decisions. Capacity dictates what and how much can be supported by a single installation. Without this information, these planners cannot precisely determine an installation's ability to accept new missions as well as decide where to move personnel and assets from closing bases. The most effective and efficient use of the Air Force's infrastructure occurs when the Air Force is able to arrange units and mission assets in a manner that enhances force presentation and power projection, while maintaining an appropriate amount of surge capacity. Senior leaders can use knowledge about installation capacity to create optimal basing solutions and reduce excess capacity, which is being unnecessarily maintained at a cost.

Problem Statement

The Air Force and the DOD have not formally defined installation capacity. The methods previously used to calculate installation capacity offer some utility; however,

these methods do not produce a consistent measure or exhibit a clear understanding of infrastructure capacity at individual installations. The indicators used in previous BRAC methods are important for capacity calculations, but this research asserts that these indicators are not exhaustive of the indicators that affect capacity. The methodology used has limitations and does not provide decisions makers with specific or accurate information. The Air Force cannot accurately assess installation capacity without a clear understanding of capacity, a consistent measure of capacity, and an appropriate set of factors to evaluate. This research will focus on defining installation capacity, determining what factors contribute to installation capacity, and applying a different method to evaluate capacity.

Investigative Questions

1. What is installation capacity?
2. What factors affect installation capacity?
3. What are the most significant factors to consider when determining installation capacity?
4. Can a metric be created to describe capacity at each installation and identify specific areas that do or do not exceed capacity?

Methodology

Urban planners use the study of human carrying capacity to determine the limits of population in modern cities and communities. Witten (2001) suggests that carrying capacity analysis can be used to determine the ability of built and natural resources to accommodate population growth. An existing method used to evaluate urban carrying capacity will be selected and applied to measure installation capacity.

Carrying capacity analysis of urban areas can be evaluated using several different methods. These methods fall into three broad categories: system, societal, and environmental based (Wei, Huang, Lam, & Yuan, 2014). An environmental-based model may be most applicable as it assesses capacity by analyzing the environmental constraints of an area or system (Wei et al., 2014). Specifically, the indicator-benchmark comparison, a type of environmental-based model, is selected in this study. The indicator-benchmark comparison method evaluates a set of capacity indicators against set thresholds and creates a carrying capacity index for each indicator. As well, the method creates an overall carrying capacity (Wei et al., 2014). Within the indicator-benchmark comparison, principle component analysis (PCA) and factor analysis (FA) are used to evaluate the capacity for the subsets of capacity indicators and principle component extraction is used to calculate a compressive capacity index (Liu, 2012).

The indicator-benchmark comparison can be applied to the study of installation capacity by establishing a unique set of indicators that influence infrastructure capacity at Air Force bases. Once the installation capacity index is created, procedures can be applied to obtain a composite capacity score. The sponsor of this research, Headquarters Air Force Logistics, Engineering and Force Protection (AF/A4) has provided Sustainable Development Indicator (SDI) and Facility Capacity Analysis (FCA) data for all Air Force installations. These data will be analyzed using common statistical software packages.

Assumptions/Limitations

This research will analyze data collected from Air Force installations. The indicators selected may not be a completely exhaustive set of measures that affect installation capacity. Unique, and sometimes unknown, attributes exist at each

installation. This research may not capture these attributes, which may limit the comprehensiveness of the capacity evaluation. Also, data are not available for every CONUS installation so any conclusions made will only be applicable to the installations included in the research.

Study Implications

The model developed in this research will provide decision makers and planners with a better understanding of infrastructure capacity at CONUS Air Force installations. The method offers a more comprehensive measure of capacity than the methods used in previous analyses and can be altered if other indicators are discovered. The research will also identify areas where excess capacity exists. The Air Force may use the results to compare installations and predict effects of major closure or realignment actions.

Document Overview

This thesis follows a traditional five-chapter format. Chapter I provided a brief overview of the topic, the research questions, and an overview of how the researcher will answer these questions. Next, Chapter II provides a literature review consisting primarily of BRAC methods and carrying capacity concepts. Chapter III then discusses the methodology used, focusing on multivariate analysis techniques. Chapter IV presents the results of the PCA and FA, as well as the composite capacity scores for individual installations. Finally, Chapter V provides a discussion and conclusion, as well as opportunities for future research.

II. Literature Review

Overview

Chapter II begins with an overview of the methods available for the DOD to reduce its physical infrastructure, followed by a review of the first four BRAC rounds, and an in-depth review of the 2005 BRAC. Specifically, the review focuses on identifying where, when, and how the DOD incorporated installation capacity measures into the BRAC analysis process and possible limitations in those analyses. The chapter continues with a history of carrying capacity studies and investigates methods used to assess human capacity. Finally, the chapter presents a survey of possible indicators to be used when evaluating installation capacity.

DOD Basing Actions

The threat against the United States (U.S.) has changed several times throughout the course of history and so has the DOD's requirement for different weapon systems and basing structures. Following the Cold War, the DOD began to assess whether or not the existing base structure matched the needs of the Department (Lockwood & Siehl, 2004). The Soviet Union's threat against the U.S. had faded and this caused the U.S. to amend their defense budget, force structure, and consequently their staffing levels in an effort to create a more efficient force and reduce operating costs. The DOD had two options to accomplish major base closure and realignment action: 10 U.S.C 2687 or BRAC.

10 U.S.C. 2687

Prior to 1977, the Secretary of Defense (SECDEF) maintained the authority to dictate the process, selection, and execution of military base closures. However, in 1977, Congress created legislation to formally establish and retain control over the process of

military base closures and realignments (United States Government Accountability Office, 2013). 10 U.S.C. 2687 defines the procedures and requirements that the DOD must adhere to before performing major basing actions. The DOD is only subject to 10 U.S.C. 2687 if a closure involves an installation with at least 300 civilian employees or if realignment reduces the civilian workforce by greater than 1,000 civilian employees or 50% of the employees at an installation (10 U.S.C. 2687). The DOD must notify Congress if their intended actions exceed the thresholds above.

Per 10 U.S.C. 2687, the DOD must submit its notification to Congress with its annual request for authorization appropriations and the notification includes multiple elements. The first element of the notification requires the DOD to evaluate the consequences of the proposed closure or realignment in several areas: fiscal, local economic, budgetary, environmental, strategic, and operational (10 U.S.C. 2687). The DOD also has a requirement to consider, at a minimum, the two following criteria:

- (1) the ability of the infrastructure (including transportation infrastructure) of both the existing and receiving communities to support forces, missions, and personnel as a result of such closure or realignment; and
- (2) the cost associated with community transportation infrastructure improvements as part of the evaluation of cost savings or return on investment of such closure or realignment (10 U.S.C. 2687)

However, the DOD has never performed a closure or realignment action under the statutory requirements of 10 U.S.C 2687. Since 1977, every DOD closure or realignment has been below the 10 U.S.C. 2687 thresholds or executed using BRAC authorization, which is a different form of legislation than 10 U.S.C. 2687 (United States General Accounting Office, 2013).

The First Four BRAC Commissions

In 1988, Congress passed the Defense Authorization Amendments and Base Closure and Realignment Act of 1988 (P.L. 100-526), which provided the DOD with an opportunity to realign their force structure and potentially close installations under separate legislation than 10 U.S.C. 2687. This Act served as the basis for additional BRAC commissions in 1991, 1993, and 1995. Throughout the first four rounds of BRAC, planners and analysts utilized similar methods to perform the capacity analysis and evaluation of the DOD's inventory. The first BRAC commission also established criteria that would be used in the successive BRAC rounds.

The Secretary of Defense (SECDEF) directed the 1988 BRAC commission to study the DOD's installation inventory and establish a methodological process for determining the most appropriate realignment and closure actions (Edwards & Ribicoff, 1988). In his charter to the commission, the SECDEF provided nine criteria to be applied when evaluating the installations (Edwards & Ribicoff, 1988). The criteria are shown in Table 1.

Specifically, criterion 1-4 evaluated the military value of an installation. Military value describes how well an installation is able to support the mission needs of the units located on the particular installation. Criterion 5 captures the requirement for return on investment and criteria 6-8 appraise the impact of BRAC actions. Criterion 9 required the DOD to develop and evaluate strategies from implementation of BRAC actions (Edwards & Ribicoff, 1988). Of these criteria, criterion 1-4 are the most important as the 1988 commission focused primarily on the concept of 'military value' when evaluating installations.

Table 1: 1988 DOD BRAC Criteria (Adapted from Edwards & Ribicoff, 1988)

Criteria	Category	Description
1	Military Value	The current and future mission requirements and the impact on operational readiness of the military departments concerned.
2	Military Value	The availability and condition of land and facilities at both the existing, and potential receiving locations.
3	Military Value	The potential to accommodate contingency, mobilization, and future force requirements at receiving locations.
4	Military Value	The cost and manpower implications.
5	Return on Investment	The extent and timing of potential cost savings, including whether the total cost savings realized from the closure or realignment of the base will, by the end of the 6-year period beginning with the date of the completion of the closure or realignment of the base, exceed the amount expended to close or realign the base.
6	Impact of BRAC	The economic impact on the community in which the base to be closed or realigned is located.
7	Impact of BRAC	The community support at the receiving locations.
8	Impact of BRAC	The environmental impact.
9	*Specific to '88	The implementation process involved.

After the 1988 commission inventoried the DOD's installation, it categorized bases with similar missions and calculated military value for each base within these mission categories. Installations received a grade of marginal, acceptable, and fully satisfactory for 21 attributes grouped in five different factors. These factors and attributes are shown in Table 2. This method helped the commission determine how well each base was supporting their assigned missions. The "Availability of Facilities" factor

primarily measured the capacity at each installation. The commission's decision of how many bases to close was based on the excess capacity that was discovered in the system (Edwards & Ribicoff, 1988). However, this measure was only evaluated using the marginal, acceptable, and fully satisfactory grading scale. The report does not state what data the commission collected, if any, to determine where excess capacity existed. The report also indicates that the commission was predominantly concerned with the availability of adequate training areas, when considering the capacity of an installation. It is possible the commission made subjective decisions about capacity, which, at the time, may have been acceptable due to the excess capacity existing in the DOD's inventory. In the end, the 1988 BRAC commission recommended completely closing 86 installations, partially closing five, and realigning 54 (Edwards & Ribicoff, 1988). The success of the 1988 BRAC led to legislation allowing for three more rounds of BRAC in the early 1990s.

The Defense Base Closure and Realignment Act of 1990 (P.L. 101-510) provided the SECDEF with three opportunities to make recommendations for base realignment and closure actions (Lockwood & Siehl, 2004). However, this legislation differed from the 1988 legislation. In the 1988 law, the SECDEF selected the members of the commission who, in turn, submitted their recommendations to the SECDEF. For the 1991, 1993, and 1995 BRACs, the President appointed an independent commission who received recommendations from the SECDEF. The 1990 Act required the SECDEF's recommendations to be based on the force structure plan and criteria that would be developed by the DOD and Congress (Department of Defense, 1991). This had the effect

of changing the process of how the criterion was formulated and how recommendations were developed, evaluated, and reviewed.

Table 2: 1988 Military Value Attributes (Adapted from Edwards & Ribicoff, 1988)

FACTORS	PHYSICAL ATTRIBUTES
Mission Sustainability	Site-Specific Mission
	Deployment Means
	Relationship to Other Activities
	Weather/Terrain/Land Use
	Survivability
	Maneuver Space
Availability of Facilities	Operations
	Support
	Infrastructure
	Administration
Quality of Facilities	Condition
	Technology
	Configuration
Quality of Life	Family Housing
	Bachelor Housing
	Recreation/Amenities
	Medical
Community Support	Work Force
	Commercial Transport
	Infrastructure
	Complementary Industry

The criteria selected for the 1991 BRAC differed slightly from the 1988 criteria because the DOD removed the ninth criterion. The list of new criteria for the 1991, 1993 and 1995 BRAC is shown in Table 3.

Table 3: 1991/1993/1995 DOD BRAC Criteria (Adapted from Lockwood & Siehl, 2004)

Criteria	Description
1	The current and future mission requirements and the impact on operational readiness of the Department of Defense's total force.
2	The availability and condition of land, facilities and associated airspace at both the existing, and potential receiving locations.
3	The ability to accommodate contingency, mobilization, and future total force requirements at both the existing and potential receiving locations.
4	The cost and manpower implications.
5	The extent and timing of potential cost savings, including the number of years, beginning with the date of completion of the closure or realignment, for the savings to exceed the costs.
6	The economic impact on the communities.
7	The ability of both the existing and potential receiving communities' infrastructure to support forces, missions and personnel.
8	The environmental impact.

Similar to the previous BRAC, the DOD focused mainly on military value as a means of evaluation (Department of Defense, 1991). Each service used the first four criteria to evaluate military value and provide recommendations to the SECDEF. The services used criteria 5 through 8 as a secondary means of evaluation. For the Air Force, the Secretary of the Air Force (SECAF) created the Base Closure Executive Group (BCEG), a group tasked with performing an equal evaluation of all Air Force installations. The BCEG began the analysis by grouping the installations into mission categories described in the force structure plan: support, training, flying/strategic, flying/tactical, flying/mobility, flying/training, flying/other, other, and air reserve (United States General Accounting Office, 1991). Following that, the BCEG conducted a

capacity analysis of each mission category. As directed by the SECDEF, if a category were found to have no excess capacity, the installations in that category were eliminated from further consideration for realignment or closure (Department of Defense, 1991). For the categories that remained, the BCEG used the eight criteria and 80 sub-elements to assess each installation. Bases were rated using a “stoplight chart” with the following standards for each sub-element: “green” meaning the base met or exceeded the standard, “yellow” meaning the base marginally met the standard, and “red” meaning the base was significantly short of meeting the standard (United States General Accounting Office, 1991). Unfortunately, the capacity analysis results, standards for the sub-elements, and grades of individual installations were classified as Secret and not included in the SECDEF’s report to the BRAC commission. The commission concluded the 1991 BRAC by recommending 43 closures and 28 realignments. The procedures and business rules used in the 1991 BRAC would be followed closely in the next two rounds of BRAC in 1993 and 1995.

For the 1993 BRAC, and as required by The Defense Base Closure and Realignment Act of 1990, the Office of the Secretary of Defense (OSD) gave closure and realignment recommendations to an independent commission, based on the same selection criteria used in 1991, and an updated force structure plan (Department of Defense, 1993). While the overall processes and roles remained the same as those in 1991, the Air Force made several slight adjustments within their own process. The 1993 BCEG began the analysis by grouping bases into five categories: flying, industrial/technical support, training, other, and Air Reserve components (United States Government Accountability Office, 1993). Each category had on average two sub-

categories. Categorizing the bases allowed the BGEG to compare the current basing structure to the force structure plan. In the next step, the BCEG used the categorization to perform a capacity analysis.

The 1993 BRAC capacity analysis involved two components--the first of which was similar to the 1991 BRAC. The BCEG compared the current basing structure to the force structure plan to identify if excess capacity existed in any of the categories. For example, the group would compare the number of fighter aircraft and wings in 1992 (current) to the number of fighter aircraft and wings in 1999 (future), as set in the force structure plan. If the 1992 figure was greater than the 1999 estimate, then the category was considered to have excess capacity (United States Government Accountability Office, 1993). However, by using this method, the BCEG assumed that the current basing structure was operating at an optimal level. If a category or sub-category did not have any excess capacity, it was excluded from further consideration for closure or realignment. The second component of the capacity analysis was what differed significantly from the previous rounds. The 1993 BCEG performed 48 site visits to determine the maximum number of aircraft or missions that a base could support (United States Government Accountability Office, 1993). The 1993 reports do not indicate what factors were considered by the BCEG or report the results and findings of the site visits. Following the capacity analysis, the BCEG applied the eight criteria to the remaining bases.

The final step in the Air Force's 1993 BRAC selection process was to score the eligible bases using the criteria shown in Table 3. The BCEG created a set of 160 sub-elements to evaluate the criteria, twice the number used in the 1991 BRAC. The group

collected data through questionnaires received from the base and major command (MAJCOM) levels. The BCEG used the data to assign a red, yellow, or green grade to each sub-element and criterion, similar to how the assessment was performed in 1991 (United States Government Accountability Office, 1993). The BCEG recommended 31 major closures, 12 major realignments, and 122 reduction actions at smaller bases. These closures and realignments, along with the first two BRAC rounds, would reduce the DOD base structure by 15% (Department of Defense, 1993). The final BRAC allowed by Public Law 101-510 occurred in 1995.

The 1995 BRAC followed the same basic procedures in the two preceding rounds but with one significant change. The DOD made an effort to identify opportunities for the services to share common assets (United States Government Accountability Office, 1995). The OSD created the Joint Cross-Service Groups (JCSG) to consider what activities and functions could be shared among the services as a way to reduce excess infrastructure. The JCSGs worked with the military departments to reduce excess capacity in five functional areas: depot maintenance, military medical treatment facilities, test and evaluation, undergraduate pilot training, and laboratories (Department of Defense, 1995). The JCSG employed an analytical tool, mixed-integer, linear programming, to optimize cross-service basing solutions and generate alternatives for decision makers. The solutions were optimized based on the parameters of military value, function value, and capacity (Department of Defense, 1995). The JCSGs performed their capacity analysis by comparing the capacities of the existing functional areas to the projected workloads. The JCSGs assessed capacity with five different measures: labor-hours, test-hours, work-years, medical centers, and available airfield

space. Although the DOD added the JCSGs and focused on joint opportunities, the Air Force's processes remained relatively unchanged from 1993.

The 1995 BCEG began their analysis by grouping the bases into seven mission categories, two more than the previous BRAC. The capacity analysis eliminated 9% of the bases from consideration because no excess capacity existed at these locations. An additional 15% were eliminated because of geographical significance. In addition, several other Air Force bases were excluded from evaluation because of high relocation costs. GAO reported that the Air Force's process in 1995 for selecting closures and realignments appeared subjective and not well-documented, a finding also stated in their 1993 report (United States Government Accountability Office, 1995). Regardless, the Air Force recommended 12 base closures and 11 realignments, which contributed significantly to the DOD's recommendation of 33 closures, 26 realignments, and 27 changes to prior BRAC decisions. Following the 1995 BRAC, Congress would not pass legislation allowing for military base closures for another 10 years.

2005 BRAC

Chapter II contains a section solely to review the 2005 BRAC because this BRAC's timeline and legislation differed significantly from the previous rounds. Between the years of 1995 and 2005, the U.S. national defense requirements and strategy changed considerably. The conflicts and enemies the U.S. encountered in the early 2000s were significantly different than what the country expected in the early 1990s--the last time the DOD performed a major overhaul on its basing structure. In 2001, Congress authorized BRAC 2005 by amending the Defense Closure and Realignment Act of 1990 and provided the DOD with another opportunity to recommend base closure and

realignment actions (United States Government Accountability Office, 2012). Although the government kept the same basic techniques used in previous BRACs, the extended timeline allowed the DOD to apply a greater degree of comprehensiveness to the analysis and selection process.

The DOD spent over two years developing the recommendations for base closures and realignments (United States Government Accountability Office, 2012). As part of their task, Congress required the Department to certify that another BRAC was necessary. As part of the congressionally mandated certification, the DOD performed a preliminary capacity analysis on its facility inventory and found that there was 24% excess capacity. Analysts calculated excess capacity by comparing 1989 base loadings to the projected loadings for 2009. In the previous rounds, this analysis dictated the number of bases to be closed. However, the 2005 BRAC utilized a different method. The DOD instead relied on The seven JCSGs and the three military departments to identify closure opportunities by following the analytical process shown in Figure 1 (Department of Defense, 2005). Similar to the previous BRACs, the capacity analysis took place early in the process.

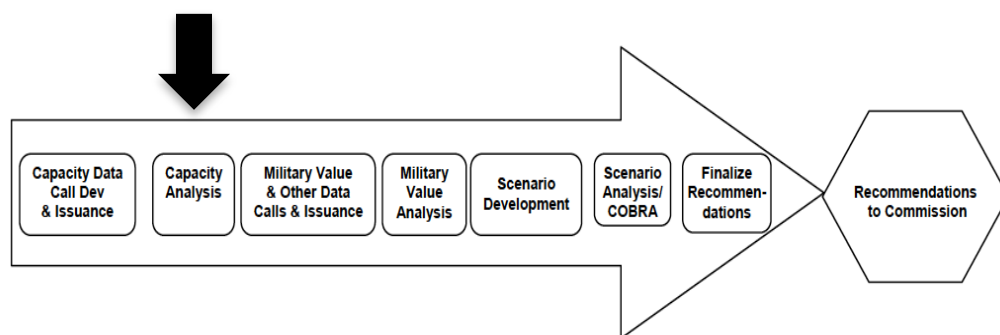


Figure 1: 2005 BRAC Analytical Process (Department of Defense, 2005)

The DOD began the capacity analysis by developing a 735-item questionnaire and distributing it to every installation in its inventory. Once complete, the installations returned the questionnaires to their respective JCSG or military department, who were then responsible for performing the calculations and evaluation of the capacity analysis. The JCSG and departments considered two types of capacity: physical and operational. Physical capacity measured property items, such as buildings and airfields. Operational capacity referred to the amount of thoroughfare or workload that could be completed at an installation (Department of Defense, 2005). Besides adding a few additional words, Congress and the DOD kept the same eight criteria used in the previous BRAC rounds. The exact language of the criterion is shown in Table 4. The first four criteria, which represent military value, remained as the primary measure to use when evaluating alternatives. The DOD recognized that military value needed to be assessed both quantitatively through data and metrics, as well as qualitatively through senior leader and military judgment (Department of Defense, 2005). The process allowed for qualitative inputs to be considered when assessing basing solutions. The departments and JCSGs each used different tools and methods to reach their recommendations.

Table 4: 2005 DOD BRAC Criteria (Adapted from Department of Defense, 2005)

Criteria	Description
1	The current and future mission capabilities and the impact on operational readiness of the total force of the Department of Defense, including the impact on joint warfighting, training, and readiness.
2	The availability and condition of land, facilities, and associated airspace (including training areas suitable for maneuver by ground, naval, or air forces throughout a diversity of climate and terrain areas and staging areas for the use of the Armed Forces in homeland defense missions) at both existing and potential receiving locations.
3	The ability to accommodate contingency, mobilization, surge , and future total force requirements at both existing and potential receiving locations to support operations and training.
4	The cost and manpower implications.
5	The extent and timing of potential cost savings, including the number of years, beginning with the date of completion of the closure or realignment, for the savings to exceed the costs.
6	The economic impact on existing communities in the vicinity of military installations.
7	The ability of the infrastructure of both the existing and potential receiving communities to support forces, missions, and personnel.
8	The environmental impact, including the impact of costs related to potential environmental restoration, waste management, and environmental compliance activities.

Michael Dominguez, the acting Secretary of the Air Force at the time of BRAC 2005, stated that BRAC 2005 gave the Air Force the “ability to reset our forces in a strategic way and create innovative organizational and basing solution” (Department of the Air Force, 2005). The Air Force’s strategy included right-sizing the operations and support functions and consolidating where possible (Department of Defense, 2005). This rationale is apparent in the Air Force’s four goals for the 2005 BRAC:

- (1) transform by maximizing warfighting capability of each squadron,
- (2) transform by realigning Air Force infrastructure with future defense strategy,

- (3) maximize operational capability by eliminating excess physical capacity, and
- (4) capitalize on opportunities for joint activity (Department of the Air Force, 2005).

The first goal led the Air Force to analyze the size of flying squadrons by consolidating fighter and mobility assets. The remaining goals resulted in the Air Force's recommendation to close 10 bases and realign 62, to include several joint-basing solutions. The Air Force developed their recommendations using the analytical process shown in Figure 1. Based on this process, the BCEG developed its own questionnaire to collect data from Air Force bases. The group used this data, as well as weapon systems templates to estimate the capacity of each installation. Following the capacity analysis, the BCEG used the results to calculate military value.

To measure military value, the BCEG assigned every CONUS installation a score for the four criteria contributing to military value, as well as a composite Mission Capacity Index (MCI) for the base (Department of Defense, 2005). The Air Force used the Web-based Installation Data Gathering and Entry Tool (WIDGET) to calculate MCIs for each base in eight different mission categories: fighter; bomber; tanker; airlift; special operations/combat search and rescue (CSAR); intelligence, surveillance, and reconnaissance (ISR); unmanned aerial vehicles (UAV); and space operations. This allowed the BCEG to evaluate each installation's capability to support every kind of Air Force mission (Department of the Air Force, 2005). The BCEG created seven categories of installation attributes that encompass military value. As shown in Figure 2, each category contributes to one of the four military value criterion in Table 4. Several attributes that were selected to calculate military value relate directly to installation

capacity. For example, airfield dimensions provided information on the maximum amount of aircraft an installation could support and unconstrained acreage measured the base's ability to expand and accommodate future growth. To calculate MCI, the Air Force assigned each attribute a score in the range of 0 to 100 and applied a pre-determined weight to the score. However, the weights varied depending on the mission being evaluated. The weighted scores were totaled to determine the overall MCI (Department of the Air Force, 2005). Once MCIs were calculated for every base, the Air Force proceeded to the scenario development and analysis phases.

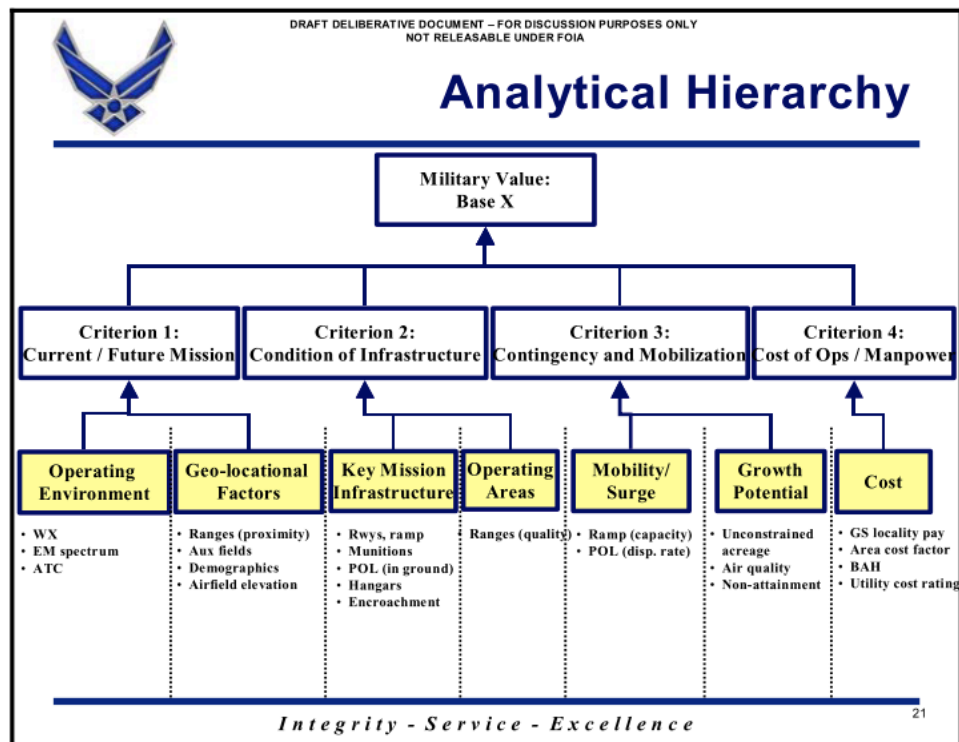


Figure 2: Military Value Hierarchy (Department of the Air Force, 2005)

During the scenario analysis phase, the BCEG used the Air Force Cueing tool to find multiple sets of basing alternatives based on the capacities, MCIs, and several

business rules. Members of the BCEG evaluated each set of alternatives to determine if the alternative was actually feasible and was consistent with the Air Force's objectives and force structure plan. Following this, the costs and savings associated with each scenario were calculated using the Cost of Base Realignment (COBRA) tool. The final step in the Air Force's 2005 BRAC process was to evaluate the remaining criteria for the bases included in the final set of alternatives (Department of Defense, 2005).

The DOD utilized the same general criteria in every round of BRAC as the basis for executing hundreds of base realignment and closure actions. However, the analytical models, data collection, and other decision support tools advanced significantly from the use of "stop-light" charts in 1988 to more rigorous methods accounting for the multi-criteria decisions in 2005. The departments used these advanced techniques to evaluate major basing decisions. Specifically, the DOD evaluated the military value of individual installations and used the measure as the primary basis for recommending closures and realignments. Despite the use of advanced techniques to evaluate military value, which included elements of capacity, several limitations exist in the methods used.

Limitations of Previous Capacity Analyses

Throughout all the BRAC rounds the methods used to evaluate capacity contained limitations such as lack of precision, assumptions, inconsistencies, and lack of completeness. Each round contained a different set of limitations, which ultimately affect the outcome of the capacity analysis. The DOD and the service departments evaluated capacity at two levels: department-wide estimation of excess capacity and the capacity at individual installations. This section details some impacts resulting from previous study limitations with regards to the two different capacity evaluation levels.

The military value attributes used in the 1988 BRAC captured several components of installation capacity: land use, maneuver space, and availability of facilities. However, the DOD evaluated these attributes using a three-point grading scale, limiting the precision of the measure. In the 1991, 1993, and 1995 BRAC, the Air Force compared the current force and basing structures to the projected force structure and determined where and how much excess capacity would exist. This method provided an estimate of excess capacity, but made the assumption that the basing structure at the time was optimized. The 2005 BRAC capacity analysis also included several limitations.

In an effort to justify the 2005 BRAC, Congress required the DOD to submit a force structure plan, infrastructure inventory, budget justification and description of excess infrastructure capacity. The DOD used capacity-to-force structure ratios to estimate that the Department had 24% excess infrastructure capacity (United States Government Accountability Office, 2013). The ratios compared a capacity indicator, such as administration facility area, with a force indicator, such as number of personnel assigned. For the 2005 BRAC, the DOD compared the 2009 ratios to the 1989 baseline ratios to estimate the amount of excess capacity. This method provided the DOD with an indication of excess capacity in the DOD's infrastructure, but lacked the precision to serve as the basis for closure or realignment actions at a specific base (United States Government Accountability Office, 2013). The DOD also assumed the 1989 base structure was appropriately sized for the force structure at that time, which limited the validity of the results. In addition to this, each service, including the Air Force, measured capacity differently (United States Government Accountability Office, 2013).

The Air Force estimated its department-wide excess capacity through two indicators: airfield and facility area. It compared the current inventory to the space requirement instead of using the 1989 ratio as a baseline (Department of the Air Force, 2005). This method improved on the DOD's because it did not assume that the 1989 basing structure was appropriately sized. Still, the estimates did not provide detailed information about infrastructure capacity at individual installations.

In its 2005 report to SECDEF, the Air Force stated the installation capacity analyses were performed by individual MAJCOMs and presented the BCEG. Following this, the BCEG used the results to identify potential closure and realignment opportunities (Department of the Air Force, 2005). However, the report did not indicate the methods used by the MAJCOMs to determine installation capacity or if there was consistency among the commands. The Air Force also did not include the results of the capacity analysis in its report to SECDEF. Furthermore, the report did not identify what attributes contribute to installation capacity or how capacity should be measured.

Although it has been a significant factor in the previous rounds of BRAC, the Air Force did not formally define installation capacity. The Air Force developed a comprehensive method for evaluating military value, but did not have a model to measure capacity. In each round, analysts evaluated a selection of capacity attributes within the military value measurement, and so installation capacity was reflected in military value. However, an analyst would not have been able to extract information about capacity from the military value measurements because the capacity attributes are combined with the other factors. This research finds that the study of *carrying capacity* can identify

additional attributes that contribute to capacity which have not been considered in previous military value assessments.

Carrying Capacity

Researchers currently study the concept of carrying capacity in several fields: range and wildlife management, chemistry, medicine, economics, anthropology, engineering and population biology (Sayre, 2008). The formalized study of carrying capacity began in the shipping industry. In the 1840's, ships paid a tax for the amount of goods brought into a port. The tax collectors used the ship's dimensions to estimate the volume of goods stored in the ships hold. These estimates became inaccurate as ships transitioned to steam-power because fuel, water, and boilers took up cargo space. To amend this problem, shippers began to use the term "carrying capacity" to describe the amount of goods a ship was able to transport, or payload, as it is referred to today (Sayre, 2008). Several decades later, individuals applied the concept of carrying capacity to the natural world.

In the late 1800's, U.S. and Australian range managers and ranchers begin using carrying capacity as a measure of range productivity. In this context, the carrying capacity estimated the amount of livestock that an area of land could sustain without deterioration. Although no specific method existed, range carrying capacity was typically a function of rainfall and available vegetation (Sayre, 2008; Young, 1998). In the 1920's, Aldo Leopold expanded the study of range carrying capacity by investigating effects of deer overpopulation in the Kibab Plateau region. This field of study would transition into what is known as game management. Previous to this research, scientists believed carrying capacity was static. However, Leopold suggested that carrying

capacity was actually dynamic, and could be controlled by manipulating the environment (Sayre, 2008). Scientists affirmed Leopold's theory as the study of carrying capacity migrated into biology and ecology.

In 1953, Eugene Odum discovered that several species' population growth followed a sigmoid curve and would typically approach and level at an upper limit. He noticed the growth curves fit closely to a logistic curve. So Odum began modeling population growth mathematically, using the constant k as the limit of the upper asymptote. He defined k as the maximum population of a species in a certain environment, also referred to as carrying capacity (Sayre, 2008). Today, ecologists and biologists continue to define carrying capacity, k , as the theoretical number of a species that an environment can support (Young, 1998). Odum, Leopold, and several other scientists have attempted to estimate human carrying capacity.

The study of carrying capacity as it relates to human population began centuries ago. In his 1798 publication "An Essay on the Principle of Population," Thomas Malthus discussed the progression of societies and the growth of world population. Malthus theorized that the earth could only provide a finite amount of sustenance to support human population. According to Malthus, if the population increased beyond what the earth could provide, a famine would occur and reduce the population to a level that matched the capacity of earth's resources (Malthus, 1798). However, Malthus never used the term carrying capacity. William Vogt was one of the earliest scientists to apply the term carrying capacity to human population. Vogt developed a mathematical method for estimating capacity that was a function of biotic potential and environmental resistance (Sayre, 2008). Even though several other methods exist to estimate human carrying

capacity, the theory is essentially the same: environmental factors and resource capacity limit human population growth. In general, human population carrying capacity is defined as “the ability of a natural or man-made system to absorb population growth or physical development without significant degradation” (Schneider, Godschalk, & Axler, 1978).

More recently, urban planners have used the concept of population carrying capacity as a tool to the study of human population limits in cities and regions. A carrying capacity analysis provides information that allows analysts and planners to identify areas where communities can, or cannot, support further development (Witten, 2001). Witten (2001) argues that carrying capacity analysis must consider the abilities of both built and natural resources to support population growth without endangering either type of resource. Built resources include man-made artifacts and systems such as transportation networks, wastewater treatment plants, and housing. Natural resources refer to systems that occur in nature, such as water and oil supplies, arable land, and wetlands. Both types of resources have carrying capacities that can be exceeded. A resource will fail at performing its intended function if a population exceeds the capacity of a given resource. Researchers evaluate a wide variety of resources when evaluating carrying capacity.

General Approaches

As world population continues to grow and natural resources deplete, researchers have become more interested in determining the limits of human population in cities, regions, and countries. However, a single methodology for evaluating population carrying capacity does not exist. Researchers assess carrying capacity using a large range

of parameters and a variety of different methods depending on the level of analysis. However, the assessments of carrying capacity can be categorized by three approaches: societal, environmental, and system (Lane, 2010).

Societal models primarily use economic and demographic factors to assess carrying capacity (Lane, 2010; Wei et al., 2014). Researchers calculate the carrying capacity of a region by comparing current demographics to government planning initiatives and policy. Societal models are limited because they discount the confines of the physical environment and neglect to consider resource supply and demand (Lane, 2010). However, environmental-based models consider the physical environment impacts and resource constraints. For this reason, many researchers prefer environmental-based models to perform carrying capacity assessments (Lane, 2010). Finally, system-based methodologies evaluate capacity-related factors within a larger framework and not in isolation, as in the other two types of models (Wei et al., 2014). These models investigate the relationship between technological, environmental, economic, and demographic factors, often over extended periods of time (Lane, 2010). From these three general models, researchers employ an array of various methods to assess urban carrying capacity (UCC).

Urban Carrying Capacity

The population planning and research community recognizes the significant role UCC plays in securing a sustainable future. Countries faced with overpopulation and resource depletion have developed several methods to evaluate UCC in cities and regions. However, literature does not provide a strong theoretical basis for how UCC should be assessed (Wei et al., 2014). Wei, et al. (2014) identified the six most typical

UCC assessment methods. The descriptions of these methods, along with their merits and limitations, are shown in Table 5. Regardless of the method selected, Wei, et al. (2014) suggest researchers consider the three following principles when developing a model:

- 1) the model should attempt to use complete and holistic information about the whole system without sacrificing important information about the subsystems,
- 2) the findings need to be simple enough for urban planners to interpret and apply to their day-to-day operations, and
- 3) the results should be communicated in a manner that is understandable across multiple disciplines and functions.

One form of UCC assessment is the indicator-benchmark system. This system is a conventional method used by researchers to assess carrying capacity (Wei et al., 2014).

Indicator-Benchmark Comparison

The indicator-benchmark comparison begins with the indicator selection. The researcher must compile a set of indicators that exhaustively and comprehensively measure the capacity or sustainability of an area (Wei et al., 2014). The indicators selected include natural and built resources an area requires to sustain life (Liu, 2012). Drinking water is one example of an indicator commonly used in UCC. Populations depend heavily on the drinking water supply to support life in the area they occupy. Of course, a researcher must consider several other indicators affecting capacity because a population needs more than just drinking water.

Table 5: Carrying Capacity Assessment Methods (Adapted from Wei et al., 2014)

Method	Description	Merits	Limitations
Energy Analysis	Based on thermodynamic concepts and general systems theory, incorporates ecological and economic factors	Holistically quantifying the contribution of natural capitals and ecological process to human activities	Strong data requirements; weak and unclear links with relevant concepts in other subjects;
IPAT Equation	$I = P \cdot A \cdot T$, I = impacts on environment, P = human population, A = affluence of human life, T = Technology of production and consumption	A general and simplified calculation of human activity impacts on the environment	The simplistic prerequisite of a multiplicative relationship among the determining factors may lead to inaccurate calculations
Graphical Model	Graphical plot of human population against time to identify growth patterns	An effective way to visually describe the trend and conditions of carrying capacity	This type of model is largely for illustrative purposes
Ecological Footprint Model	Assesses amount of land area needed to sustain a region, compares to the availability of ecological productive land	An initiative-appeal and standardized model to quantify demand and supply on the world's ecosystem	This method is more applicable at the global level, but not for population concentrated areas
PSR and DPSIR model	Pressure-State-Response, tracks causality process of environmental degradation	An effective framework to choose and organize indicators	The model focuses on the interactions between the environment and the economy, whilst other links such as links between the environment and the society are not adequately addressed
Indicator-Benchmark Comparison	Carrying capacity values are compared with threshold, acceptable, minimum, or recommended standards	The logic of the estimation procedure is easy to understand	Assessment results are subjective to the selection of indicators and evaluation criteria

Once a set of indicators is selected, the value of each indicator must have a sustainable threshold to be compared against. A sustainable threshold reflects the established standard, sustainable state, or maximum capacity of an indicator. These thresholds can be referred to as carrying capacities. During a carrying capacity analysis, the current value of each indicator is compared to its associated threshold value (Wei et al., 2014). Continuing with the example of drinking water, urban planners might specify a volume of water that an area can supply for drinking each day. If the demand for drinking water exceeds this value, the sustainable threshold, the environment will eventually fail to support the population. Following this comparison between the sustainable threshold and current demand, researchers can create a composite index for the overall carrying capacity by aggregating each indicator's carrying capacity (Wei et al., 2014). Indicator-benchmark comparisons follow this general framework, but specific models often vary depending on the researcher, population of interest, and environmental characteristics.

Researchers have created several different assessment systems to evaluate carrying capacity in a given city or region—and no two systems are the same. The selection of indicators will vary from study to study because environmental constraints and resource availability differ and researchers have different opinions on what factors contribute to a sustainable population. The subjective selection of indicators is a limitation of the indicator-benchmark comparison, as shown in Table 5.

This study performed a literature review on several indicator-benchmark comparison studies and compiled a set of indicators that could potentially be used to assess installation capacity. Table 6 contains indicators found in published literature that

were used by researchers to assess carrying capacity at the urban and regional levels (Graymore, Sipe, & Rickson, 2010; Lane, Dawes, & Grace, 2014; Liu, 2012; Oh, Jeong, Lee, Lee, & Choi, 2005; Yishao, Hefeng, & Changying, 2013). Table 7 contains indicators used in previous BRAC capacity and military value analysis (Department of the Air Force, 2005; Department of the Army, 2005). This research will review the indicators presented in Table 6 and Table 7 to select the applicable indicators to measure installation capacity. However, an operational definition of installation capacity must be developed prior to the indicator selection. The Air Force has not formally defined installation capacity. The definition of installation capacity will be addressed in Chapter III.

Table 6: Potential Indicators from Literature

Indicator	Source		Indicator	Source		Indicator	Source
Energy	(Oh et al., 2005)		Percentage of Industrial Land	(Yishao et al., 2013)		Water Consumption per Capita	(Graymore et al., 2010)
Green Areas			PM ₁₀ Emission Intensity			CO2 Emissions	
Water Supply			Rate of Industrial Waste Water up to the discharge standards			Percent Wastewater Treated to Tertiary Level	
Sewage Treatment			Potential Geological Disasters			Amount of Effluent Reused	
Waster Treatment			Comprehensive Index of Water Quality			Amount of Solid Waste Produced per Person	
Climate variability	(Lane et al., 2014)		Rate of Good Ambient Air Quality			Percent of Waste Recycled	
Liquid Fuel			Per-Capita Area of Construction			Total Nitrogen in Water	
Infrastructure			Per-Capita Water Resource			Total Phosphorous in Water	
Nature Reserve			Per-Capita Water Consumption			Total Suspended Solids in Water	
Floor Area Ratio	(Yishao et al., 2013)		Per-Capita Urban Road Area	(Liu, 2012)		Faecal Coliforms in Water	
Development Land per Capita			Per-Capita Greenland Area			Annual Mean Ambient Air Concentration of SO2	
Residential Land per Capita			Volume of Industrial Water Water Discharge			Annual Mean Ambient Air Concentration of CO	
Land Subsidence			Volume of Industrial SO2 Emission			Annual Mean Ambient Air Concentration of NO2	
Suitability of natural foundation for construction			Land Clearing Rate	(Graymore, Sipe, & Rickson, 2010)	Annual Mean Ambient Air Concentration of PM		
Economic Density			Percent of Land Modified				
SO ₂ Emission Intensity			Percent of Remnant Land Remaining				

Table 7: Potential Indicators from Military Analysis

Indicator	Source		Indicator	Source
Ramp Area and Serviceability	(Department of the Air Force, 2005)		Annual Training/Mobilization Barracks	(Department of the Army, 2005)
Runway Dimension and Serviceability			General Instructional Facilities	
Level of Mission Encroachment			Enlisted Unaccompanied Personnel Housing	
Hangar Capability - Small Aircraft			Depot Maintenance	
Sufficient Explosives-sited Parking			Ammunition Storage	
Sufficient Munitions Storage			General Administrative Space	
Buildable Acres for Industrial Operations Growth			Small Unit Headquarters	
Buildable Acres for Air Operations Growth			Large Unit Headquarters	
Hangar Capability - Large Aircraft			Specialized Labs and Testing Areas	
Certified Weapons Storage Area			Air Quality Attainment	
Maneuver Areas; heavy and light	(Department of the Army, 2005)		Off-Installation Zones with Incompatible Land Use Matrix	
Airspace Attributes			Buildable Acres	
Fixed Wing Runway, Surfaced			Land Owned/Controlled by Installation	

III. Methodology

Chapter Overview

This chapter explains the methodology used to evaluate installation capacity. First, this research defines installation capacity and selects the indicators for the analysis. Next, Chapter III describes the data used and how the data was handled and prepared. Following this, the chapter provides an explanation of principal component analysis and exploratory factor analysis. Finally, a model is created to estimate the composite capacity score of individual installations. The results of the research are presented in Chapter IV.

Defining Installation Capacity

The Air Force considered installation capacity during the BRAC 2005, but never formally defined the term. In order to define installation capacity, the term must be dissected. The Department of Defense defines military installation as a “base, camp, post, station, yard, center, homeport facility for any ship, or other activity under the jurisdiction of the Department of Defense, including any leased facility (Department of Defense, 2015).” Merriam-Webster defines capacity as the ability to hold or contain people or things. In the context of an Air Force installation, the people are the military members, base employees, and dependents residing on the installation. The things refer to aircraft, military equipment, and other weapons systems required to support the installation’s mission. Another concept to consider is carrying capacity, which was defined in Chapter II. Using these definitions, an operational definition of installation capacity can be proposed:

Installation capacity is the maximum quantity of mission assets and personnel that a base’s built and natural infrastructure can support without significant degradation to the installation’s mission and personnel’s quality of life.

Installation Capacity Index

The first step of this methodology is to create an index for measuring installation capacity. The index must consist of indicators that contribute to the definition of installation capacity. The researcher selected the indicators based on the literature review and subjective judgment of factors that contribute to installation capacity. Liu (2012) and Wei, Cui, Li, and Xie (2015) developed a comprehensive carrying capacity indexes to assess major cities in China. Each index was divided into components with several indicators assigned to each component. The indicators represented resource supply and demand for each component. Following this framework, an installation capacity index will be developed and divided into different “components.” Each component contains a set of indicators.

Installation Capacity Index Components

The indicators used to evaluate carrying capacity vary depending on the scale, location, and application of the study. However, Oh, et al. (2005) determined that researchers generally divide carrying capacity into four determining components: environmental and ecological, urban facilities, public perception, and institutional. The first two components of environmental and ecological and urban facilities are especially relevant to installation capacity; the latter two components of public perception and institutional factors are not in the scope of this research. The environmental and ecological component describes the environment’s ability to support human activity without significant degradation. Likewise, the urban facilities component considers the ability of facilities and services to support human activity without being degraded (Oh et

al., 2005). These two components will serve as the basis for determining the appropriate components of the installation capacity index.

Using information from the literature review and a knowledge of installation-specific indicators, this research adapted Oh, et al.'s (2005) classification to the context of Air Force installations and created four components. The first component, environment, reflects the degree to which the environment can support the activities at an Air Force installation without substantial degradation. The next three components of infrastructure, space, and mission operations are adapted from Oh, et al.'s (2005) urban facilities component to fit the context of measuring capacity at military installations. The infrastructure component measures the ability of an installation's utility systems to support base personnel and mission assets. The space component includes major physical area factors. Finally, the mission operations component reflects the ability of an installation to support flying operations. Table 8 summarizes the components of the installation capacity index. The next step is selecting the most appropriate indicators that contribute to each component.

Table 8: Installation Capacity Components

Component	Definition
Environment	The ability of an installation's environmental systems support human and mission-related activities without significant degradation to the quality of life or mission success
Infrastructure	The ability of an installation's utility systems to support human and mission-related activities without significant degradation to the quality of life or mission success
Space	The ability of installation's physical space and facilities to support human and mission-related activities without significant degradation to the quality of life or mission success
Mission Operations	The ability of installation's infrastructure to support aviation activities without significant degradation to mission success

Indicator Selection

An appropriate set of indicators must be selected to represent each component. Table 6 in Chapter II presented a list of indicators used by researchers to evaluate carrying capacity in different regions and cities. Also in Chapter II, Table 7 lists the factors used by the Air Force and Army to evaluate capacity in previous BRACs. Using these two tables, and in conjunction with knowledge of available data, the researcher selected indicators for each component, beginning with the environment component. The following sections detail the indicators selected for each component. Each indicator is described, labeled, and provided the unit of measure used in the study.

Environment Indicators

According to Godschalk and Alxer (1977), several factors affect the environmental carrying capacity of an area such as air and water quality, protected resources, natural hazards, condition of land and soil, and energy availability. In the context of military installations, other factors could include noise pollution from aircraft and solid and hazardous waste. Of these factors, the Air Force primarily collects data on air quality and energy, which will be considered in the infrastructure component. Thus, based on the data available, the following indicators represent the environment component:

X_1 : Permitted Air Pollutants (tons per year)

X_2 : Emitted Air Pollutants (tons per year)

Permitted air pollutants is a cumulative total of particulate matter, carbon monoxide, sulfur dioxide, and nitrogen oxides that are permitted by EPA at an installation. Emitted air pollutants is the volume of air pollutants emitted at each installation. The pollutants measured in X_1 and X_2 are a set of the six “criteria pollutants” identified in the Clean Air Act (United States Environmental Protection Agency, 2007) and are known to cause health, environmental, and property damage. The six pollutants are particulate matter (PM), ground-level ozone, carbon monoxide (CO), sulfur oxides (SO₂), nitrogen oxides (NO_x), and lead (United States Environmental Protection Agency, 2007). However, the Air Force does not have data for lead or ozone pollution. The Air Force collects data on volatile organic compounds (VOC), which create ozone when reacted with NO_x. However, VOC was not included when calculating X_1 and X_2 because the concentration

of VOCs is not directly proportional to the amount of ozone created (Swackhamer, 1991). Therefore, X_1 and X_2 both include four of the six air pollutants: PM, CO, SO₂, and NO_x.

Infrastructure Indicators

The infrastructure component includes the traditional utility systems installed at a military installation. These systems contribute significantly to installation capacity because each provides a necessary resource. Water, electricity, and sanitary services are essential for mission operations and sustaining quality of life. This research considers the water, wastewater, and electricity utility systems with the following indicators:

X_3 : Water Quantity Supply (gallons per day)

X_4 : Water Quantity Average Demand (gallons per day)

X_5 : Wastewater Discharge Capacity (gallons per day)

X_6 : Wastewater Discharge Average Demand (gallons per day)

X_7 : Electrical Power Supply (MW)

X_8 : Electrical Power Average Demand (MW)

Water quantity supply is the amount of water available to the installation either through local utilities or on-base source and the demand is the total quantity of water consumed by the personnel, facilities, and operations of the installation. Wastewater discharge capacity is the maximum volume per day of sanitary waste that the servicing wastewater treatment plant(s) are able to process. The wastewater discharge demand variable represents the average amount of sanitary waste generated. Electrical power supply is the total capacity that can be supplied to the base from the local utility and the demand reflects average, not peak, conditions.

Space Indicators

The space component measures the degree to which an installation's physical area and facilities can support human and mission-related activities, while the mission operations component covers facilities that directly support the flightline mission. The space component captures the general facility and physical space properties of an installation. This component is comprised of the following indicators:

X₉: Administrative Facility Space Inventory (square feet)

X₁₀: Administrative Facility Space Occupied (square feet)

Besides flightline-related facilities, the majority of mission and support activities at an installation occur in administrative facilities. Also, administrative facilities are typically a dominant space constraint compared to other facilities types. Another set of important indicators regards the total area available for further development and construction.

X₁₁: Total Base Area (Acres)

X₁₂: Developed or Constrained Base Area (Acres)

Total base area reflects the area owned by each installation. Developed or constrained area refers to land that cannot be built on because of existing facilities or environmental restrictions (e.g. wetlands, clear zone, cultural site). The final set of indicators used in the space component considers dormitories.

X₁₃: Total Dormitory Rooms (# of rooms)

X₁₄: Required Dormitory Rooms (# of rooms)

The required dormitory rooms reflect the number of enlisted members requiring a dormitory room on a base.

Mission Operations Indicators

The mission operations component is similar to the space component but considers facilities and infrastructure related directly to the Air Force's aviation mission. The following indicators reflect the major facilities that support flightline operations:

X₁₅: Runway Dimensions (square yards)

X₁₆: Required Runway Area (square yards)

X₁₇: Apron Dimensions (square yards)

X₁₈: Required Apron Area (square yards)

The runway and apron dimension indicators reflect the total area of active runway(s) and apron space at an installation. The number and type of aircraft determines the required runway and apron area at an installation. In addition to these airfield pavement indicators, this component contains indicators measuring maintenance hangar space.

X₁₉: Maintenance Hangar Area (SF)

X₂₀: Required Maintenance Hangar Area (SF)

Figure 3 provides a graphical representation of the installation capacity index. A total of 20 indicators to represent the four components environment, infrastructure, space, and mission operations were selected for this study. Indicator data was collected for each installation under evaluation.

Data Collection and Preparation

Each installation being evaluated required data for every indicator specified in the installation capacity index. This section describes how the data was collected and how the researcher handled missing values and outliers. Data were collected for stateside

installations only because this research was performed in context of BRAC and 10 U.S.C. 2687, which only apply to CONUS installations.

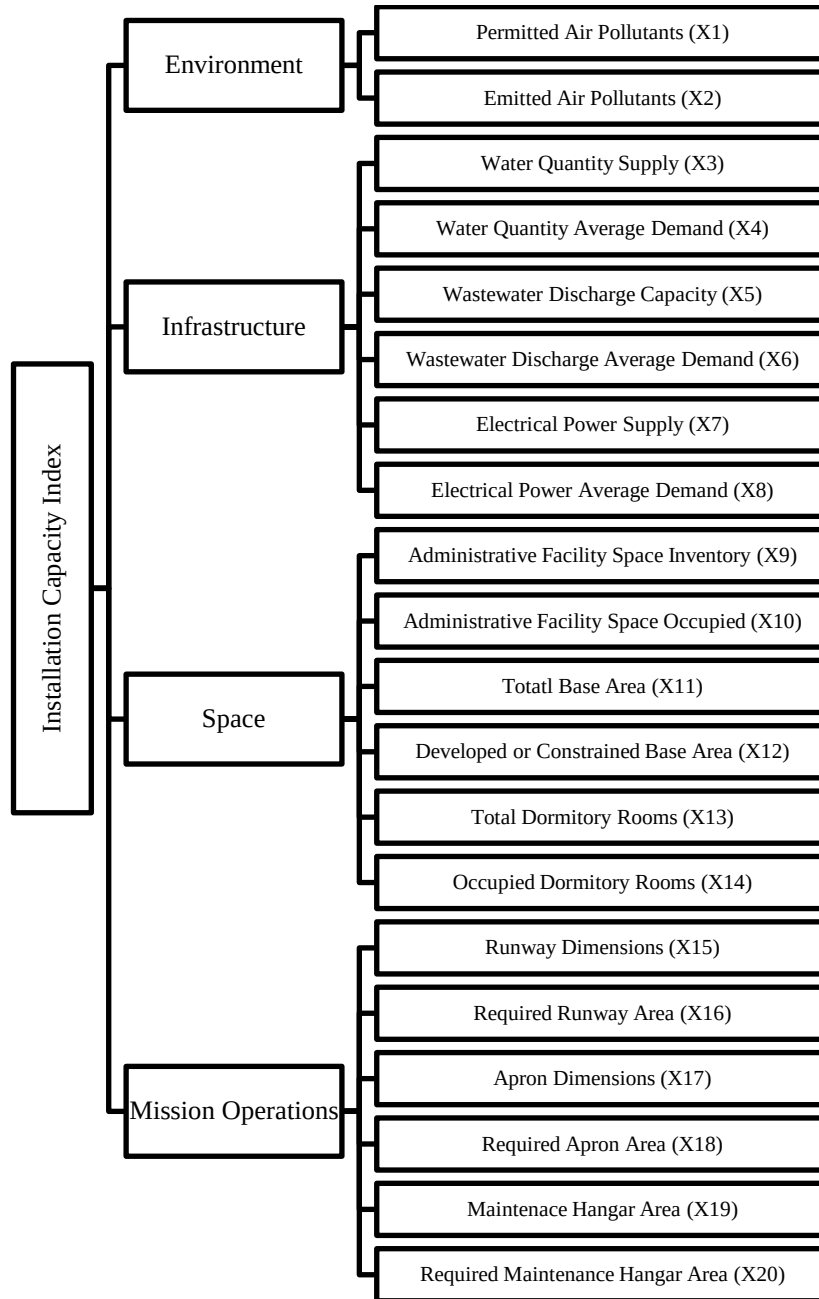


Figure 3: Installation Capacity Index

Selecting an Appropriate Method

To determine the most appropriate method of analysis, the researcher used the Steven's classification system. The Steven's method suggests data analysis methods based on the number and types of dependent variables and independent variables (Afifi, May, & Clark, 2003). In this research, the independent variables are the indicators in the installation capacity index and the data for each variable is in the form of a ratio number. Currently, there are no measures of installation capacity, so no dependent variables will be used in the initial analysis. The Steven's system suggests four types of multivariate analysis for this configuration: correlation matrix, principal component analysis (PCA), factor analysis (FA), and cluster analysis (Afifi et al., 2003). This research will focus specifically on applying PCA and exploratory factor analysis (EFA) to the data.

Principal Component Analysis (PCA)

Although PCA and EFA share several similarities, the methods will produce different results. PCA is considered an exploratory type of multivariate analysis that is used as a dimension reduction technique. The method simplifies a set of correlated variables by transforming those independent variables into a set of new, uncorrelated variables, called principal components. The principal components attempt to explain as much of the total variance in the data set as possible and are arranged in order of decreasing variance (Afifi et al., 2003). In contrast, the factors in EFA focus on the common variance shared between factors. The major differences are a result of PCA and EFA having unique models.

PCA Model

PCA is based on the theory that measured variables serve as the basis for creating the principal components (Decoster & Hall, 1998). This is shown by the direction of the arrows in Figure 4, where C_i represents the principal components and X_j represents the measured variables. The correlations between principal components and variables are referred to as the loadings, and are represented in Figure 4 by $\lambda_{p,m}$. The principal components are formed through a linear combination of the original variables.

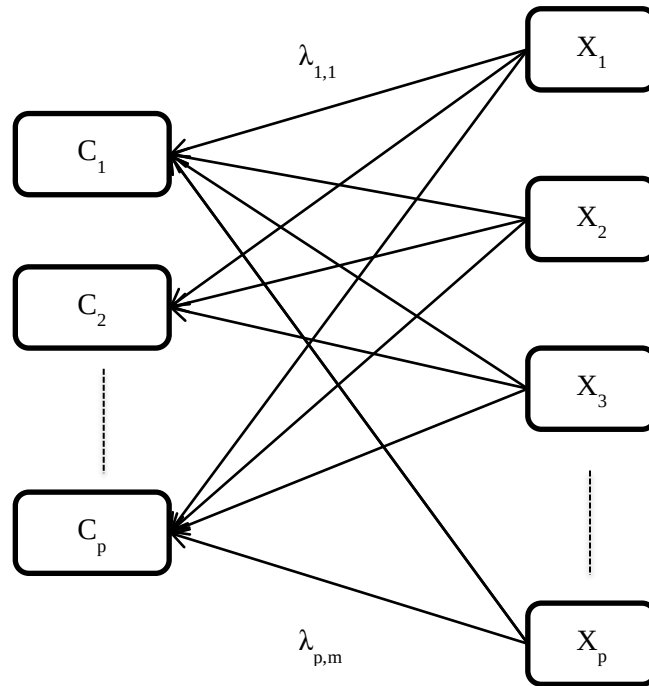


Figure 4: PCA Model (Adapted from Decoster & Hall, 1998)

For a set of P independent variables, PCA will create no more than P principal components. The principal components, C , are a linear combination of the independent variables, X as shown in the following equations:

$$\begin{aligned}
C_1 &= a_{11}X_1 + a_{12}X_2 + \dots + a_{1p}X_p \\
C_2 &= a_{21}X_1 + a_{22}X_2 + \dots + a_{2p}X_p \\
C_p &= a_{p1}X_1 + a_{p2}X_2 + \dots + a_{pp}X_p
\end{aligned} \tag{1}$$

Each component explains a portion of the original variance. That is, through PCA, components can be created that account for the dispersion within the data. The coefficients of the principal components, a , must form components that meet three requirements (Afifi et al., 2003):

1. Variance (C_1) $\geq$ Variance (C_2) $\geq \dots$ Variance (C_p)
2. Each principal component is uncorrelated with other principal components
3. The sum of squares for each component equals one (i.e., $a_{11}^2 + a_{12}^2 + \dots + a_{1p}^2 = 1$)

The components are obtained by finding the eigenvalues and eigenvectors of the either the covariance or correlation matrix. Each eigenvalue-eigenvector pair represents a principal component. Once the components are created, the researcher determines the appropriate number of components to retain through a dimensionality assessment. For a complete discussion on principal component creation, see Dillon and Goldstein (1984).

Dimensionality Assessment

PCA creates a set of principal components equal to the number of original variables. However, this is not always helpful since the dimensionality is not reduced. Reducing the dimensionality of the data eliminates computational difficulties associated with large datasets and enables better interpretation and understanding of the data. A major step in PCA and EFA is determining the appropriate number of components to retain for further analysis.

Several methods exist that can be used as heuristics when determining the appropriate number of components to retain. This research will evaluate three of those methods. The first, Kaiser's Criterion, is one of the more popular methods for selecting which components to retain. Using this criterion, factors that have an eigenvalue greater than one are retained. Another method is the graphical approach referred to as Cattell's scree test. This method requires that the eigenvalues are sorted in descending order, placed on a scree plot, and have a line drawn along the bottom set of eigenvalues. The points that remain above the "elbow" of the scree plot are retained. The third method is Horn's Curve. Horn's Curve algorithm plots a curve on the eigenvalue scree plot. Similar to scree test, this method suggests that factors above the Horn's Curve line be retained (Dillon & Goldstein, 1984). The researcher considered the recommendations of all three methods when determining the number of components to retain. After the dimensionality assessment has been made, the factor loadings can be obtained and interpreted.

Component Loadings

The component loadings represent the correlation between a principal component and an original, measured variable. The loadings vector of a principal component, Λ_m , is calculated using the eigenvector, δ_m , and the eigenvalue, V_m :

$$\Lambda_m = \sqrt{\delta_m} V_m \quad (2)$$

Loadings are calculated for each component and combined to form a loadings matrix. The researcher determines which variables have the closest relationship to a certain component or factor by identifying the variable with the highest loading value. As a heuristic, loadings with an absolute value greater than 0.5 were considered to be

significant. The researcher is then able to determine if a pattern exists in the variables that loaded heavily on a factor and attempt to interpret the meaning of the factor's variables (Dillon & Goldstein, 1984).

Component Scores

The final step of PCA is to calculate the component scores. The scores allow the researcher to compare how observations rank relative to one another within each principal component. Also, the researcher can analyze the scores of different components by plotting components against one another and identifying patterns, clusters, and outliers. The component scores, S , are calculated using:

$$S = zE \quad (3)$$

Where z is the standardized, original data and E is the matrix of eigenvectors from the correlation matrix. Although PCA calculates component scores differently than EFA calculates factor scores, the two methods share several similarities.

Exploratory Factor Analysis

EFA is a method that seeks to identify and describe the underlying and unobservable constructs that influence a set of responses (Decoster & Hall, 1998). Similar to PCA, EFA uses the correlations between observed variables to build a new set of variables that are smaller than the original (Dillon & Goldstein, 1984). Essentially, the goal of EFA is to simplify a set of complex relationships and discover the “common factors” that affect the response.

EFA Model

EFA is based on the Common Factor Model. The theory of this model is that each measured response, or variable, is influenced by a set of common factors, as well as

a unique factor. This theory is what differentiates FA and PCA. In the PCA model, the responses influence the components being created, which is the opposite of the Common Factor Model (Decoster & Hall, 1998). Figure 5 presents a graphical representation of the Common Factor Model. The direction of the arrow represents the direction of influence. The X_i terms represent the observed, or measured variables. The CF_j terms are the common factors that influence the measured variables. The e_i terms are the unique factors that also influence the measured variables. The unique factor can be

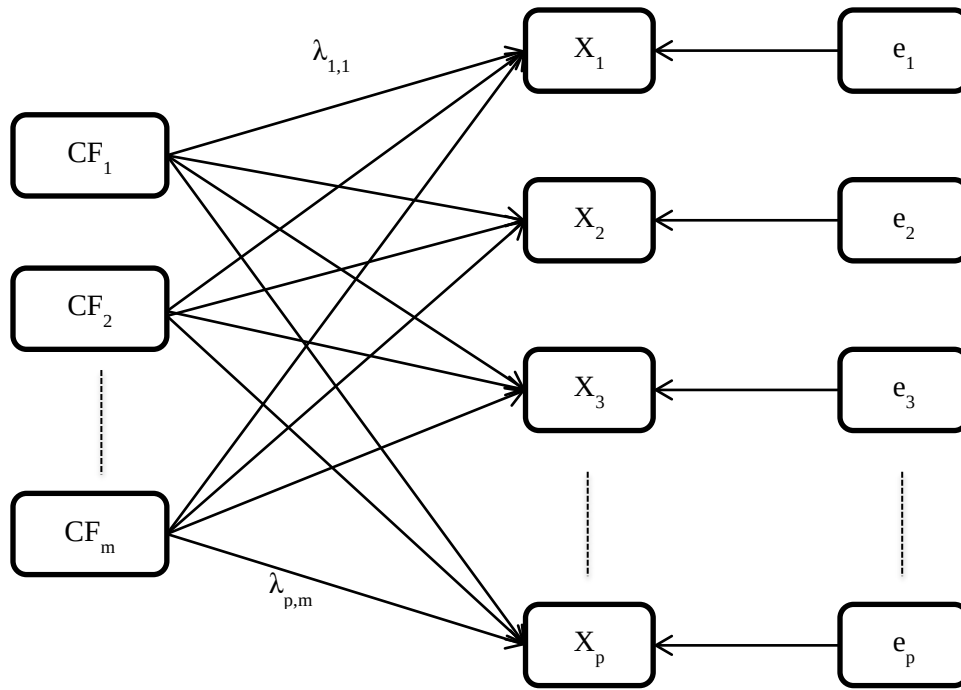


Figure 5: Common Factor Model (Adapted from Decoster & Hall, 1998)

thought of as an error term. The $\lambda_{i,j}$ terms represent the weight of j^{th} common factor on the i^{th} measured variable. These values are referred to as the factor loadings and are a significant component of the EFA model.

In EFA, the measured variables are composed of two pieces: the influence from common factors and the influence from a unique factor. This is reflected in the basic

mathematical model shown in Equation 4, where X is the vector of observed variable, Λ is the matrix of factor loadings, f is the vector of common factors, and e is the vector of unique factors.

$$X = \Lambda f + e \quad (4)$$

Considering this basic model, the variance in the measured variable must equal the variance from the common factors and the variance from the unique factor (Dillon & Goldstein, 1984):

$$var(X) = var(\Lambda f) + var(e) \quad (5)$$

The variance from the common factors, Λf , is referred to as the communality. The variance of e accounts for the remaining variance not explained by the common factors and is referred to as the uniqueness or error. The first step in obtaining the vectors and matrix shown in equation 12 is to calculate the correlation matrix and determine the number of common factors to retain.

EFA follows the same procedures used in PCA to obtain the factors and perform the dimensionality assessment. The eigenvalues and eigenvectors of the correlation matrix form the factors. Since the principal components will be identical to the initial factors, the dimensionality assessment also produces identical results. In EFA, there are two methods available to calculate the factors loadings: the principal factor method and the maximum likelihood method (Dillon & Goldstein, 1984). This research utilizes the principal factor method to extract the factors and compute the loadings, which is also identical to how the loadings are obtained in PCA. However, EFA provides additional

benefit in cases where the loadings appear to be difficult to interpret. Rotating the factors in EFA may provide a solution that is easier to interpret, without manipulating the data.

Factor Rotation

In EFA, analysts rotate the original factor loadings to help with interpreting the results. Rotating the factors does not change the data; rotation simply provides the researcher with another perspective of the data. Two methods can be used to rotate factors: orthogonal and oblique. This research employs the Varimax, orthogonal rotation method when rotating the factors. The orthogonal rotation method rotates the factors but keeps each factor perpendicular to the others, as they were originally (Dillon & Goldstein, 1984). Rotating the factors will change the eigenvalues and variances explained for individual factors. However, the communalities and total variance explained remain the same. After the rotation, the method described in the previous section can be used to interpret the loadings. The final step of EFA is to calculate the factor scores.

Factor Scores

Computing and plotting the factor scores can provide additional insight into the variables. Scores represent the placement and ranking of individual observations on the a factor (Dillon & Goldstein, 1984; DiStefano, Zhu, & Mindrila, 2009). The factor scores, F , are calculated using the following equation:

$$F = zR^{-1}\Lambda \quad (6)$$

Where z is the standardized, original data, R is the correlation matrix, and Λ is the rotated loadings matrix. Plotting the scores for multiple factors can help the researcher identify

patterns. Specifically, clusters and outliers can be identified to see how observations score in relation to one another.

Baseball Analogy

An analogy between factor scores and a baseball-pitching machine can help further explain the meaning of factor scores and how those scores are incorporated in this research. In Figure 6, the pitching machine represents a factor produced from the EFA methodology. The box of baseballs represents the different observations analyzed, which are installations in this research. Each baseball, or installation, exhibits specific characteristics and properties. Depending on the combination of these characteristics and defining properties, the pitching machine will launch the baseball onto a certain location on the wall, leaving a mark. The complete set of marks represents the scores of the observations within a particular factor. These scores are often plotted with other scores to compare and learn about the data. Typically, the generation and plotting of the factor scores completes the EFA. However, this research seeks to develop a single set of scores to evaluate capacity. This task involves combining each “score wall” into one set of scores, referred to as the installation composite capacity (ICC) in this research.

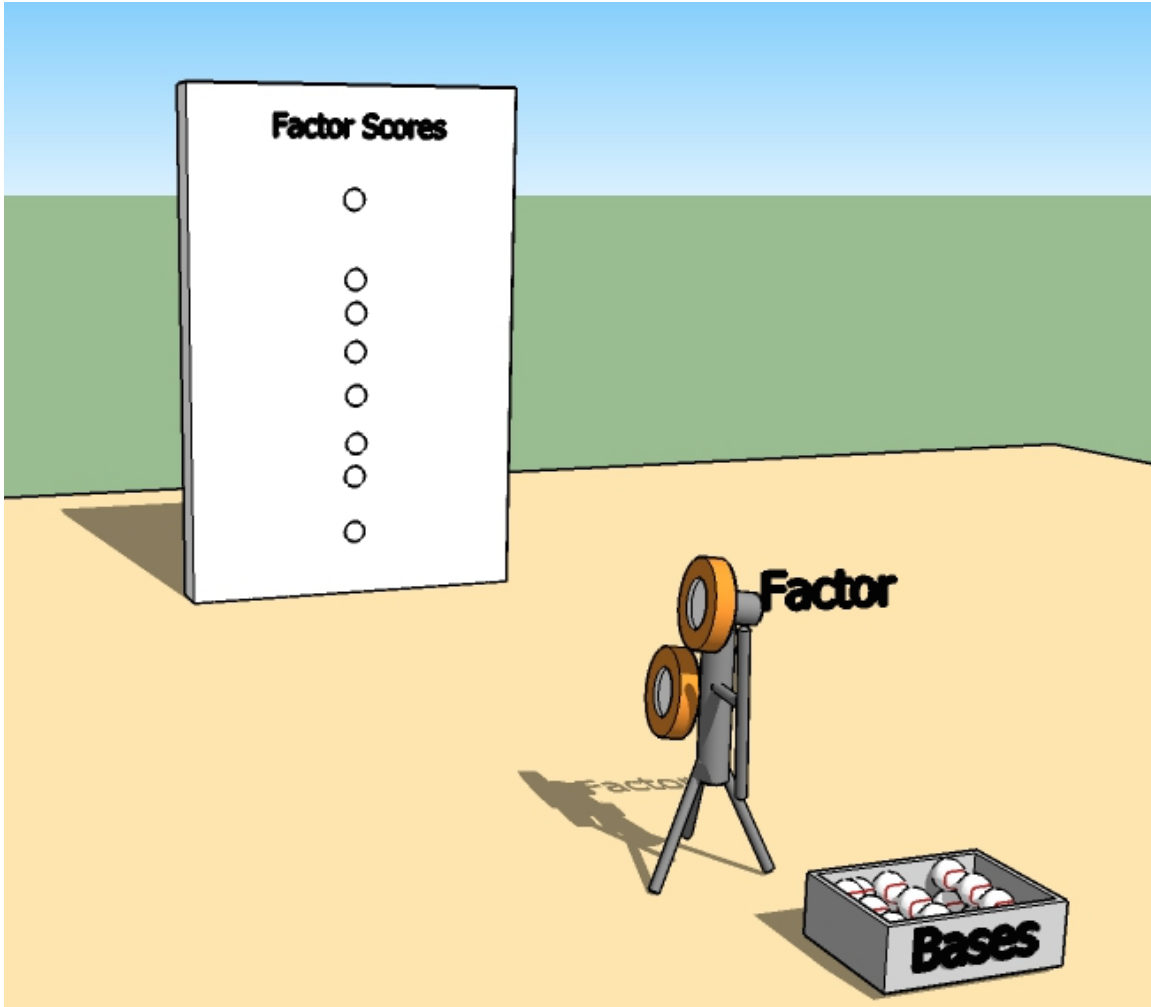


Figure 6: Factor Score Baseball Illustration

Installation Composite Capacity

EFA produces factor scores that represent measures of the observations for a particular factor. However, EFA does not produce a composite score for each observation. By combining the scoring functions of each factor, this research creates an ICC scoring model that produces a single value of capacity for each installation. This measure considers both the supply and demand variables, and thus, can provide a decision maker with the capacity “health” at each installation and a way to objectively compare installation capacities. The composite capacity score can also be used as a

dependent variable in future research. The first step of determining the composite score is to properly normalize the data.

Normalization

The data contains several different units and is divided into supply and demand categories. To address these issues, Liu (2012) and Wei, Cui, Li and Xie (2015) suggest using min-max normalization. Min-max normalization standardizes the data through two different transformations. The first applies to the supply variables and is shown in Equation 14. These variables, if increased, would improve the capacity index. So within each supply variable, the highest value will be transformed to one. The second transformation is shown in Equation 15 and applies to the demand variables. These variables, if increased, would have a negative effect on the capacity index if increased (Liu, 2012; Wei et al., 2015). So within each demand variable, the highest value will be transformed to zero.

Supply variables:

$$y_{ij} = (x_{ij} - \min(x_j)) / (\max(x_j) - \min(x_j)) \quad (7)$$

Demand variables:

$$y_{ij} = (\max(x_j) - x_{ij}) / (\max(x_j) - \min(x_j)) \quad (8)$$

Where $i = 1, 2, \dots, n$, $j = 1, 2, \dots, m$, y represents the transformed data, x represents the original data, n is the number of installations, and m is the number of indicator variables.

After the transformation, EFA may be performed.

Installation Composite Capacity

An objective of this research is to create a single measure of capacity that can be used to compare installations. This research refers to that measure as the *Installation Composite Capacity*, or *ICC*. To create the ICC, EFA is applied to the normalized supply and demand indicator variables. The EFA produces scores for each factor retained. The ICC is a composite score that reflects a combination of the individual factor scores. However, the factor scores cannot be added together to obtain the composite score. The factors explain different amounts of the total variance, and thus, must be weighted. To determine the weights, the eigenvalue of each rotated factor are divided by the sum of the rotated factor eigenvalues:

$$\omega_i = \frac{\lambda_i}{\sum \lambda_i} \quad (9)$$

Where ω_i represents the weight of each rotated factor and λ_i represents the rotated eigenvalues, for i factors. Knowing the weight of each factor, the weighted factor scores can be added to obtain the composite capacity score:

$$ICC = \sum_{i=1}^n \omega_i \Delta_i \quad (10)$$

Where Δ_i represents the vector of factor scores for each individual factor and n represents the number of factors. The ICC measures the overall capacity performance at an installation based on that installation's factor scores and the weights of those factors. The rotated factor loadings can also be used to estimate the weights of each variable in the composite score.

Indicator Weights

To gain further insight into the data, the respective weights of each factor indicator variables can be estimated from the EFA results. Calculating the weights of the

individual variables can provide an alternate means of computing a composite score. However, this research will only estimate the weights of the variables to gain insight into each indicator's contribution to the ICC score. To estimate the variable weights, the Organization for Economic Co-Operation and Development (OECD) (2008) suggest squaring each factor loading and scaling by the sum of squares within each respective factor. The squared factor loadings represent the amount of variance explained by a variable within a factor. Following this, the highest squared factor loading for a variable is multiplied by its respective factor loadings. The estimated weight of each variable is obtained by dividing these individual products by the sum of all the products.

Summary

This chapter presented a definition of installation capacity. Using this definition, a set of appropriate indicators was selected and data was collected. The data was evaluated using PCA and EFA. Finally, a model was created to estimate the ICC at each installation. The results and analysis of this methodology are presented in the following chapter.

IV. Results

Chapter Overview

This chapter contains the results of the PCA, EFA, and composite scoring analysis. Each section in this chapter describes the variables used for the analysis and presents an overview of the results. Specifically, the analysis considered the supply variables, demand variables, demand-capacity ratios, excess capacity, and the supply and demand variables together, which is referred to as the ICC variables. Finally, this chapter concludes with presenting the ICC scores for each installation in the analysis. Chapter V provides an interpretation of the results.

Collecting and Preparing Data

This research utilized five major sources of data: a 2005 BRAC database, the Sustainable Development Indicator (SDI) database, Air Force Installation Development Plans (IDP), an Air Force Real Property database, and the Facility Capacity Analyzer (FCA) database. The Office of the Secretary of Defense (OSD) maintains the 2005 BRAC database and it is publicly available at http://www.acq.osd.mil/brac/Datacall_Databases.html. AF/A4 provided access to the SDI, real property, and FCA databases. Air Force Civil Engineer Center (AFCEC) provided the IDPs. In some instances, the researcher used open-source data, such as state air permit repositories and FAA websites, to verify the data provided from the major sources. To complete the research, data was collected for all 20 variables shown in Figure 7.

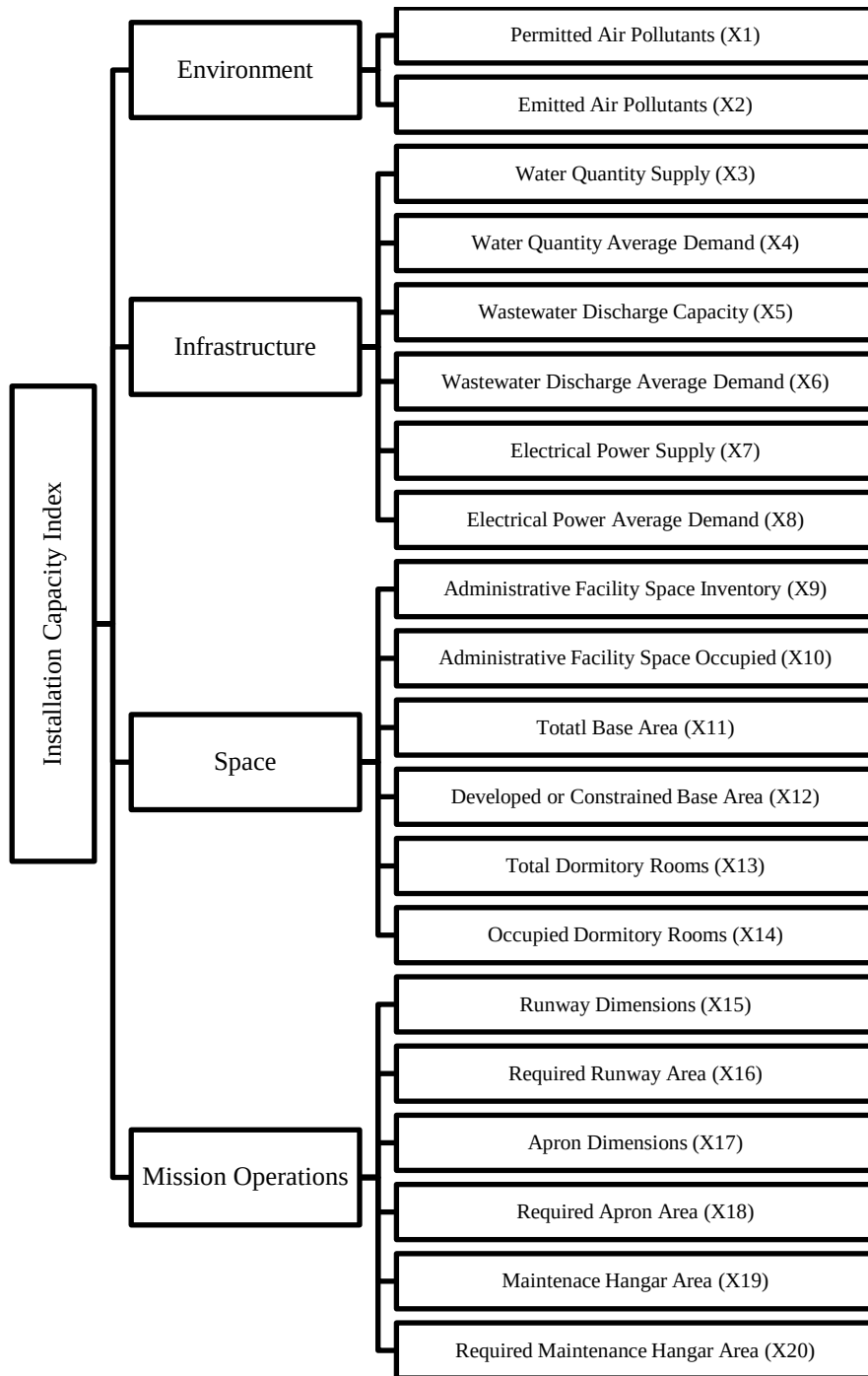


Figure 7: Installation Capacity Index

The data collection process began by retrieving the SDI data for CONUS Air Force installations because this source contained the majority of the data needed. This initial data pull included 79 installations. However, the final analysis only considered 48 installations due to the lack of data associated with the remaining 31 installations. The SDI database provided the majority of data for variables X_1 thru X_6 . The data were verified with the available IDPs and state issued air permits. If the sources provided conflicting information, this research assumed the IDP data to be the most accurate and current. The IDPs provided the majority of data for variables X_7 and X_8 . For the installations without an IDP, the data for these variables were pulled from the SDI and 2005 BRAC databases. Approximately one-third of the data for variables X_9 and X_{10} came from the IDPs. Using the administrative facility data from the Real Property database, this research populated the remaining data for X_9 . However, no source was found to contain the missing values in X_{10} . This research used nearest neighbor regression to estimate these missing value. Nearest neighbor regression is explained later in this chapter. The data for X_{11} and X_{12} came from the SDI, IDP, and 2005 BRAC databases. X_{13} and X_{14} data was primarily pulled from the SDI database. In addition, the IDP provided supplementary data to complete missing values and verify the SDI data. The FCA database provided data for variables X_{15} thru X_{20} . However, the FCA database was built using Air Force Real Property data, which created discrepancies with the information provided in the IDPs. Several installations, such as Kirtland AFB and Peterson AFB, share runways with local municipalities. In these instances, the Real Property data reflects that the installation has no runway, because the Air Force does not own the runway. Instead of inputting null values in these cases, this research used the

runway dimension values provided in the IDPs for variables X_{15} and X_{16} . In addition, the National Flight Data Center (NFCD) database was used to verify airfield dimensions. Following the data collection, the data was prepared for analysis.

In order to perform the analysis, the data was arranged in an $n \times p$ matrix, shown in following equation:

$$I_{n \times p} = \begin{bmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{bmatrix} \quad (11)$$

Where n represents the cities, each with p indicator variables.

Once in this form, the researcher was able to identify missing data and apply appropriate methods to estimate missing values.

Missing Values

The methods used in this research require a complete dataset containing continuous data and no missing values. Imputation refers to the set of processes used to replace missing values with estimations (Batista & Monard, 2002). There are several imputation techniques researchers can use to treat missing data. To treat missing values, the researcher applied k -nearest neighbor (k -NN) regression. This method predicts continuous attributes by finding k most similar instances, or nearest neighbors, in the data. Nearest neighbors are found by calculating and sorting the Euclidean distances, d , between an observation vector of missing values, x , and a set of training data vectors, y . The formula for Euclidean distance, d , is:

$$d = \sqrt{\sum_{i=1}^k |x_i - y_i|^2} \quad (12)$$

The missing value of a vector, x_m , is replaced with the mean of the k nearest neighbors (Tutz & Ramzan, 2015). The mean of the corresponding nearest neighbor values is:

$$x_m = \frac{1}{k} \sum_{j=1}^k y_j \quad (13)$$

The only missing values present in the data existed in X_{10} , Administrative Facility Space Occupied. The nearest neighbor method estimated the values by finding the mean of the three closest neighbors, based on distance from two variables: X_9 , administrative facility space inventory and total workforce. Table 9 shows the results of the nearest neighbor regression.

Table 9: Nearest Neighbor Regression Results

Installation	X10		Installation	X10		Installation	X10
Dyess	417,759		Davis Monthan	558,699		Langley	2,260,254
Edwards	1,362,586		Dover	202,384		Little Rock	417,759
Andrews	1,577,444		Eglin	1,577,444		MacDill	1,828,555
Malmstrom	316,410		Ellsworth	417,759		Mountain Home	316,410
Maxwell	971,277		FE Warren	417,759		Offutt	1,577,444
McGuire	417,759		Goodfellow	202,384		Patrick	1,828,555
Travis	490,701		Hanscom	971,277		Seymour-Johnson	316,410
Buckley	417,759		Hill	1,577,444		Sheppard	676,493
Cannon	316,410		Holloman	417,759		Tinker	1,828,555
Columbus	202,384		Kirtland	1,362,586		Vance	202,384

Outliers

The outlier analysis was the final step of data preparation. This analysis identified outliers within each indicator variable. Once identified, each value was investigated and a decision was made on how to treat the outlier. If the researcher could verify that the value was legitimate, it remained in the dataset. However, the researcher applied his judgment to remove outliers that may have been a result of inaccurate data collection or were so extreme they may have a significant effect on the analysis. Outliers were identified using Tukey's schematic boxplot.

Tukey's boxplot identifies outliers based on distance from the interquartile range (IQRs). The IQR is defined as the difference between the first (Q_1) and third (Q_3) quartiles (Dawson, 2011). Once the IQR is established, "fences" can be created to identify outliers in the data. The limits of the fences are calculated using:

$$Upper Fence = Q_3 + 3 * IQR \quad (14)$$

$$Lower Fence = Q_1 - 3 * IQR \quad (15)$$

Values that fall above or below these fences are considered to be extreme outliers and were investigated on an individual basis (Dawson, 2011). Following the treatment of missing values and outliers, the data were analyzed using several multivariate techniques.

Supply Variables

The supply variables represent the limit or threshold of capacity at the installations. These variables reflect the maximum capacity of an installation without considering the current demand at the installation. Specifically, the variables included in this section and described in the previous chapter are X_1 , Permitted Air Pollutants; X_3 ,

Water Quantity Supply; X_5 , Wastewater Discharge Capacity; X_7 , Electrical Power Supply; X_9 , Administrative Facility Space Inventory; X_{11} , Total Base Area; X_{13} , Total Dormitory Rooms; X_{15} , Runway Dimensions; X_{17} , Apron Dimensions; and X_{19} , Maintenance Hangar Area.

Outliers

Several of the supply variables contain extreme outliers. For each outlier identified, the researcher investigated and verified the value. If the value could not be verified or seemed unreasonable, the researcher removed the installation before proceeding with the analysis. In this research, all the outliers remained in the dataset except for two instances. The electrical power supply at Hill AFB (1468 MW) and the permitted air pollutants at Edwards AFB (103,424 tpy) could not be verified and are orders of magnitude higher than the other installations. For this reason, Hill AFB and Edwards AFB were removed for this analysis, leaving 46 installations for the remaining analysis. The complete list of outliers is located in Appendix A.

Dimensionality Assessment

The dimensionality of this dataset was determined using information about the eigenvalues from the correlation matrix. Table 10 contains the eigenvalues, in descending order, along with the percentage of variance explained by each component and the cumulative variance.

Table 10: Supply Indicator Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	2.89	29	29
2	1.62	16	45
3	1.45	15	60
4	1.22	12	72
5	0.92	9	81
6	0.63	6	87
7	0.56	6	93
8	0.46	5	98
9	0.16	2	99
10	0.09	1	100

Figure 8 shows a scree plot of the eigenvalues listed in Table 10, along with Horn's Curve. Both Kaiser's Criterion and Horn's Curve suggest retaining four components/factors for PCA and EFA. Based on these criteria, the researcher retained the four components bolded in Table 10 for further analysis. These four components account for approximately 72% of the variance in the data.

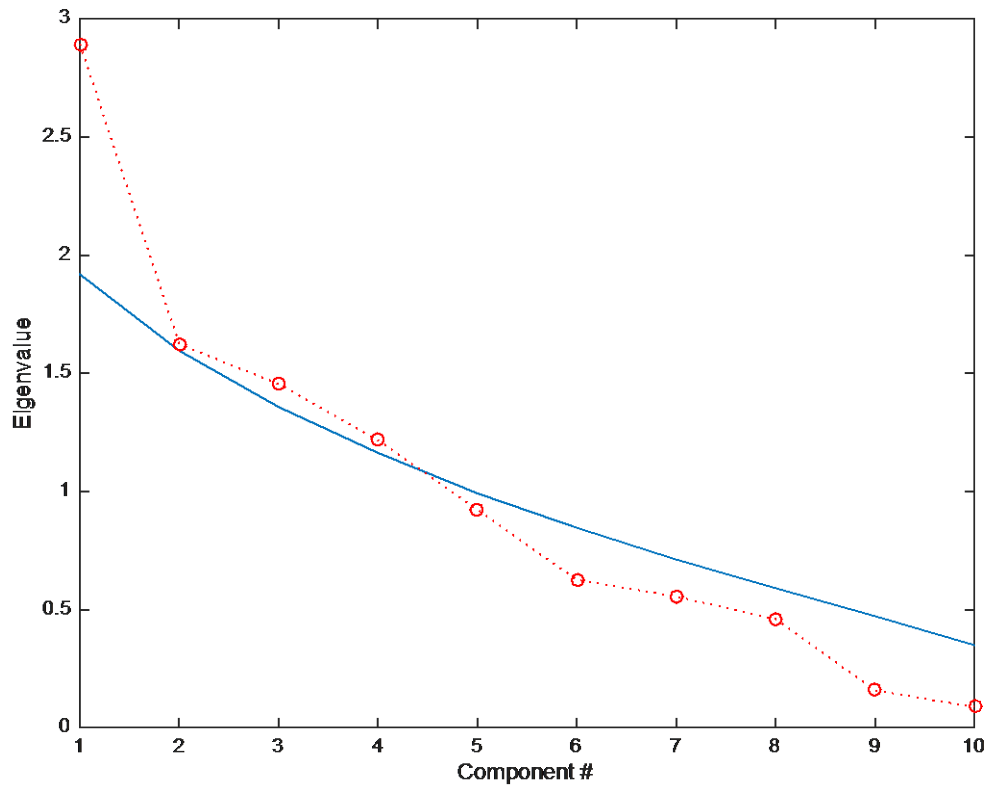


Figure 8: Supply Variable Scree Plot

PCA

The two major results to consider in PCA and EFA are the loadings matrix and score plots. Table 11 presents the PCA loadings matrix for the supply variables. The loadings represent the correlation of the component with the original variable. In Table 11, the loadings with absolute values greater than 0.5 are highlighted. All the variables load heavily onto at least one principal component, except for the total dormitory rooms variable. Also, several instances of cross loading exist in the loadings matrix. Cross loading occurs when a variables loads heavily onto multiple components. The factors are difficult to interpret based on the variable groupings.

Table 11: Supply Variable PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Permitted Air Pollutants	<u>-0.694</u>	-0.427	<u>-0.521</u>	-0.042
Water Quantity	0.015	<u>-0.522</u>	0.262	0.005
WW Discharge Capacity	-0.409	-0.457	<u>0.588</u>	0.061
Electrical Power Supply	<u>-0.735</u>	-0.253	0.246	0.162
Admin Facility Inventory	<u>-0.518</u>	-0.072	0.120	<u>0.673</u>
Total Base Area	<u>-0.634</u>	-0.142	<u>-0.674</u>	-0.174
Total Dorm Rooms	-0.408	0.450	0.392	-0.185
Runway Dimensions	-0.457	-0.099	0.285	<u>-0.688</u>
Apron Dimensions	<u>-0.662</u>	<u>0.580</u>	0.057	-0.216
MX Hangar Area	-0.469	<u>0.568</u>	-0.040	0.384
Eigenvalue	2.894	1.624	1.454	1.217

The scores of each component were calculated and plotted with the scores of the other components. Of the six plots created, only two of the score plots provided insight and information about the data. Figures 9 and 10 show score plots of the first principal component compared with the second and third principal components.

These plots both exhibit a central cluster of installations surrounded by an array of other points. The researcher distinguished the installations by total workforce. The central clusters appear to only contain bases with fewer than 9,000 employees and the outliers are primarily bases with workforces of 9,000 employees or greater. However, three installations with smaller workforces have scores similar to the bases with larger workforces.

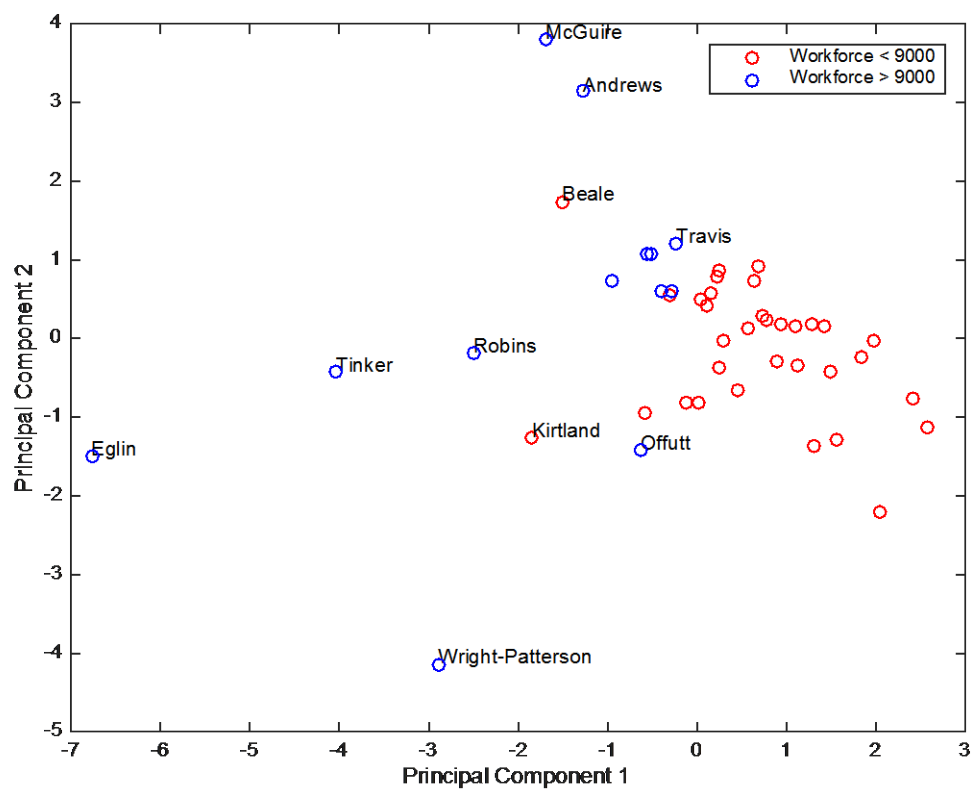


Figure 9: Supply Variable PCA Score Plot 1

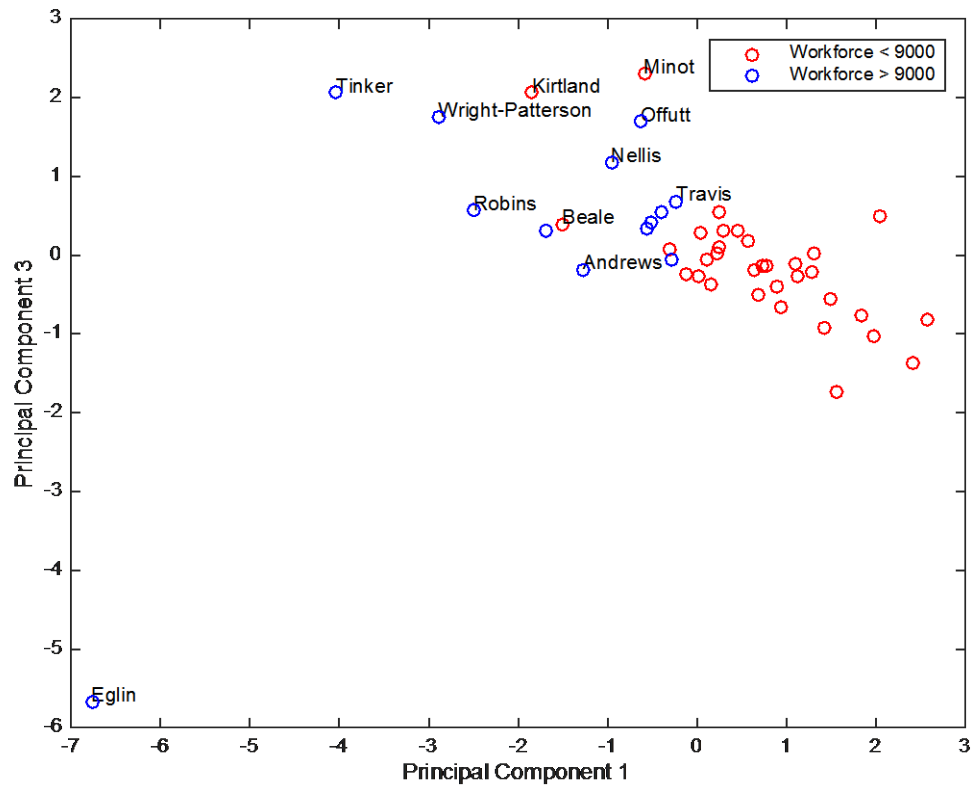


Figure 10: Supply Variable PCA Score Plot 2

EFA

Based on the dimensionality assessment, the researcher retained four factors for further analysis. The un-rotated factor loadings shown in Table 12 match the loadings of the four principal components.

Table 12: Supply Variable EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>-0.694</u>	-0.427	<u>-0.521</u>	-0.042	0.937
Water Quantity	0.015	<u>-0.522</u>	0.262	0.005	0.341
WW Discharge	-0.409	-0.457	<u>0.588</u>	0.061	0.726
Electrical Power Supply	<u>-0.735</u>	-0.253	0.246	0.162	0.690
Admin Facility Space	<u>-0.518</u>	-0.072	0.120	<u>0.673</u>	0.741
Total Base Area	<u>-0.634</u>	-0.142	<u>-0.674</u>	-0.174	0.907
Total Dorm Rooms	-0.408	0.450	0.392	-0.185	0.557
Runway Dimensions	-0.457	-0.099	0.285	<u>-0.688</u>	0.774
Apron Dimensions	<u>-0.662</u>	<u>0.580</u>	0.057	-0.216	0.824
MX Hangar Area	-0.469	<u>0.568</u>	-0.040	0.384	0.692
Eigenvalue	2.894	1.624	1.454	1.217	7.189

As seen in the PCA loadings matrix, every variable but one (total dormitory rooms) loads heavily onto at least one factor. Also, several instances of cross loading exist. The factors are difficult to interpret based on the current loading patterns. However, the rotated loadings matrix shown in Table 13 provides greater insight into the common factors.

Table 13: Supply Variable EFA Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	-0.196	-0.026	<u>-0.939</u>	0.130	0.937
Water Quantity	<u>-0.524</u>	-0.238	0.021	-0.102	0.341
WW Discharge	<u>-0.829</u>	0.142	0.006	0.136	0.726
Electrical Power Supply	<u>-0.578</u>	0.294	-0.349	0.385	0.690
Admin Facility Space	-0.297	0.028	-0.149	<u>0.793</u>	0.741
Total Base Area	0.119	0.113	<u>-0.937</u>	0.042	0.907
Total Dorm Rooms	-0.077	<u>0.726</u>	0.121	0.097	0.557
Runway Dimensions	-0.408	<u>0.584</u>	-0.248	-0.452	0.774
Apron Dimensions	0.142	<u>0.847</u>	-0.231	0.185	0.824
MX Hangar Area	0.263	0.450	-0.072	<u>0.644</u>	0.692
Eigenvalue	1.698	1.964	2.039	1.488	7.189

Following the rotation, every variable loads heavily onto one factor only. This analysis shows that factor 1 represents utility systems, factor 2 represents dorms and airfield pavements, factor 3 represents natural infrastructure, and factor 4 represents workplace facilities. After the rotation, the loadings exhibit a Kaiser's Index of Factorial Simplicity (IFS) of 0.61, which corresponds to a mediocre, but acceptable model. Kaiser's IFS measures the simplicity of the factor loadings matrix on a scale of 0, which is the worst performing model, to 1, which represents a situation where each variable only loads onto one factor (Kaiser, 1974). As a heuristic, if the IFS is greater than 0.5, the model is considered to be acceptable. Further, the factor score plots shown in Figures 10, 11, and 12 provide an understanding about installation's capacity strengths and weaknesses. These plots provide a visual depiction of capacity that analysts and planners can use to gain a level of understanding that may not be present by examining raw data. The plots

show the rankings of the installations within each factor and provide an objective means to compare specific areas of installation capacity. For example, Figure 10 indicates that Wright-Patterson AFB has the highest utility capacity of the installations considered. However, that installation has an average amount of airfield pavements and dormitories. In the same figure, McGuire AFB has the highest score for airfield pavement and dormitories, meaning that this installation has a large airfield and dormitory inventory. However, Figure 11 also shows that McGuire has one of the lowest utility scores, which mean McGuire's utility capacity is much less than the other bases examined. Figure 12 and Figure 13 can also be used to compare and contrast facility, utility, and airfield pavement and dormitory capacities.

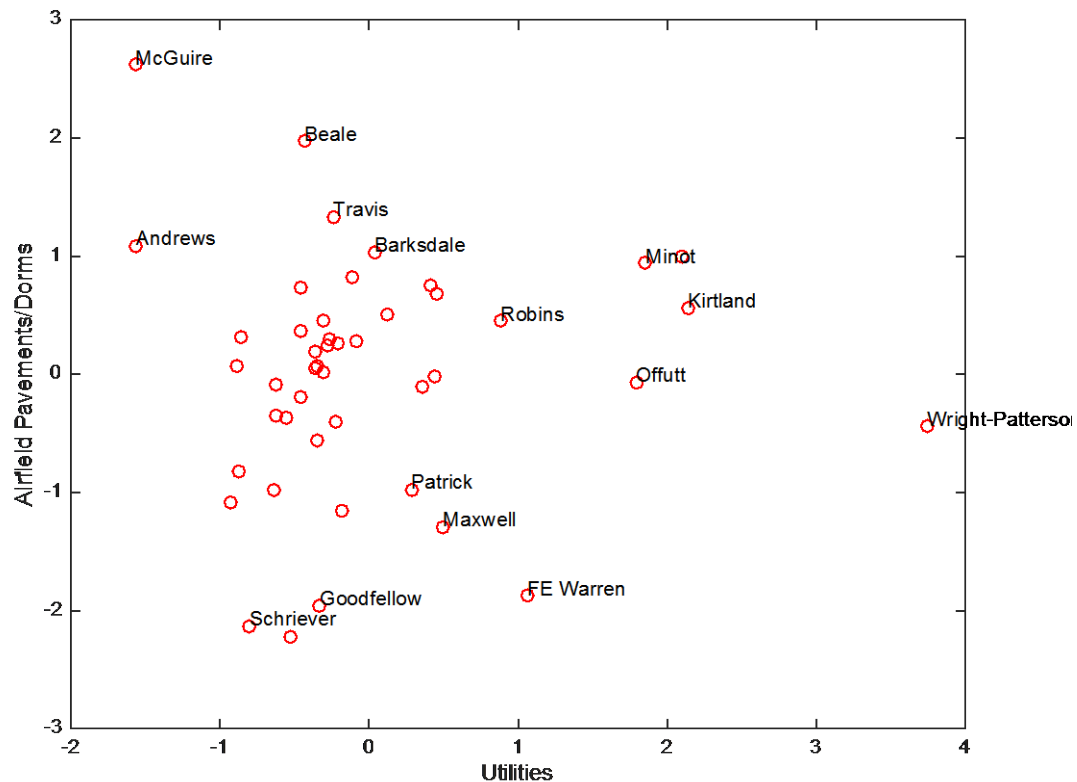


Figure 11: Supply Variable EFA Score Plot 1

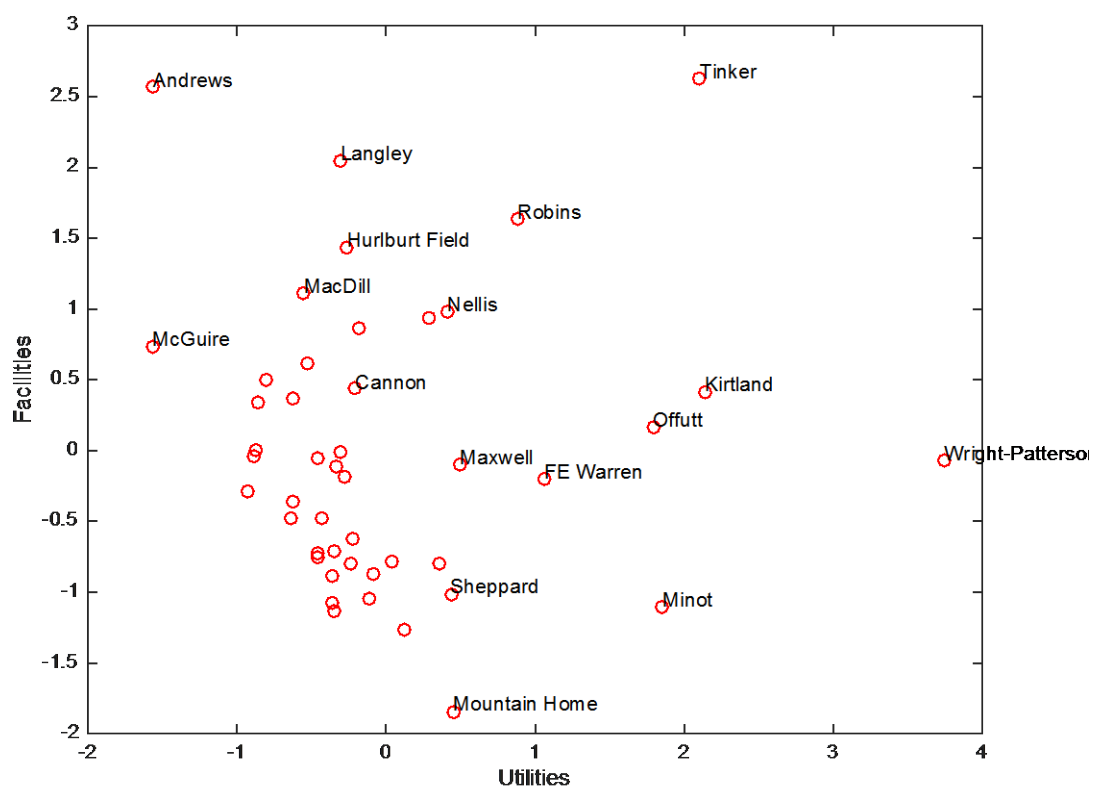


Figure 12: Supply Variable EFA Score Plot 2

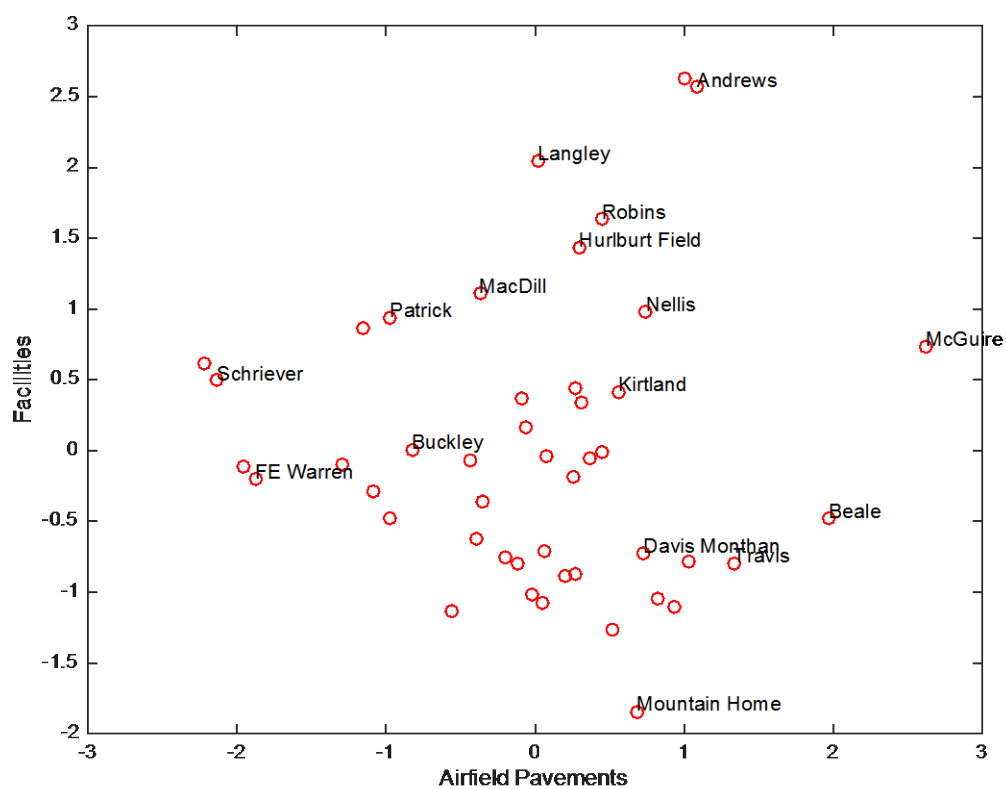


Figure 13: Supply Variable EFA Score Plot 3

Demand Variables

The demand variables represent the load on each supply indicator described in the previous section. Specifically, the variables included in this section are X_2 , Emitted Air Pollutants; X_4 , Water Quantity Average Demand; X_6 , Wastewater Discharge Average Demand; X_8 , Electrical Power Average Demand; X_{10} , Administrative Facility Space Occupied; X_{12} , Developed or Constrained Base Area; X_{14} , Required Dormitory Rooms; X_{16} , Required Runway Area; X_{18} , Required Apron Area; and X_{20} , Required Maintenance Hangar Area. The same methods of outlier analysis, dimensionality assessment, PCA, and EFA used in the previous section were applied to these demand variables. However, the results of the PCA and EFA are inclusive, and thus, not presented in this chapter. The results of the demand variable analysis are located in Appendix B.

Demand-Capacity Ratio

This research considered several combinations of the supply and demand variables. The first method used demand-capacity ratios as the variables in the PCA and EFA methods. The researcher calculated the demand-capacity ratio by dividing each demand variable by its corresponding supply variable. For example, the air pollutant demand-capacity ratio was found by dividing Emitted Air Pollutants (X_2) by Permitted Air Pollutants (X_3). The researcher applied the same methods used in the previous sections to the demand-capacity ratio variables. The results of the PCA and EFA are inconclusive, and thus, not presented in this chapter. The results of the demand-capacity ratio analysis are located in Appendix C.

Excess Capacity

This research also used PCA and EFA to examine excess capacity. The researcher created the excess capacity variables by subtracting each demand variable from its corresponding supply variable. The results of the PCA and EFA are inconclusive, and thus, not presented in this chapter. The results of the excess capacity analysis are located in Appendix D.

Installation Composite Capacity

This section presents the results of the analysis on all 20 supply and demand variables used to generate the Installation Composite Capacity (ICC) score. Previous analysis looked at supply only, demand only, or another configuration of supply and demand. This analysis assesses all 20 variables at once in order to develop the ICC scoring model. After removing the outliers, the researcher applied the PCA and EFA techniques to analyze the data. The results of the EFA were used to create the ICC scoring model.

Outliers

The outliers identified in this section of the analysis match those identified when analyzing the supply and demand variables separately. Therefore, the same bases were excluded from this analysis. Hill AFB's electrical power supply (X_7) and Edward AFB's permitted air pollutants (X_{20}) are extreme outliers and could not be verified. For this reason, Hill AFB and Edwards AFB were removed for this analysis, leaving 46 installations and 20 variables for the analysis. The complete list of outliers is located in Appendix E.

Dimensionality Assessment

The dimensionality of this dataset was determined using information about the eigenvalues from the correlation matrix. Table 14 contains the eigenvalues in descending order, along with the percentage of variance explained by each component and the cumulative variance.

Table 14: ICC Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	5.36	27	27
2	3.64	18	45
3	2.48	12	57
4	2.07	10	68
5	1.20	6	74
6	1.08	5	79
7	0.83	4	83
8	0.67	3	87
9	0.61	3	90
10	0.44	2	92
11	0.38	2	94
12	0.32	2	95
13	0.28	1	97
14	0.24	1	98
15	0.15	1	99
16	0.13	1	99
17	0.08	0	100
18	0.03	0	100
19	0.01	0	100
20	0.01	0	100

Figure 14 shows a scree plot of these eigenvalues, along with Horn's Curve. In this figure, the first four components all lie above the Horn's Curve.

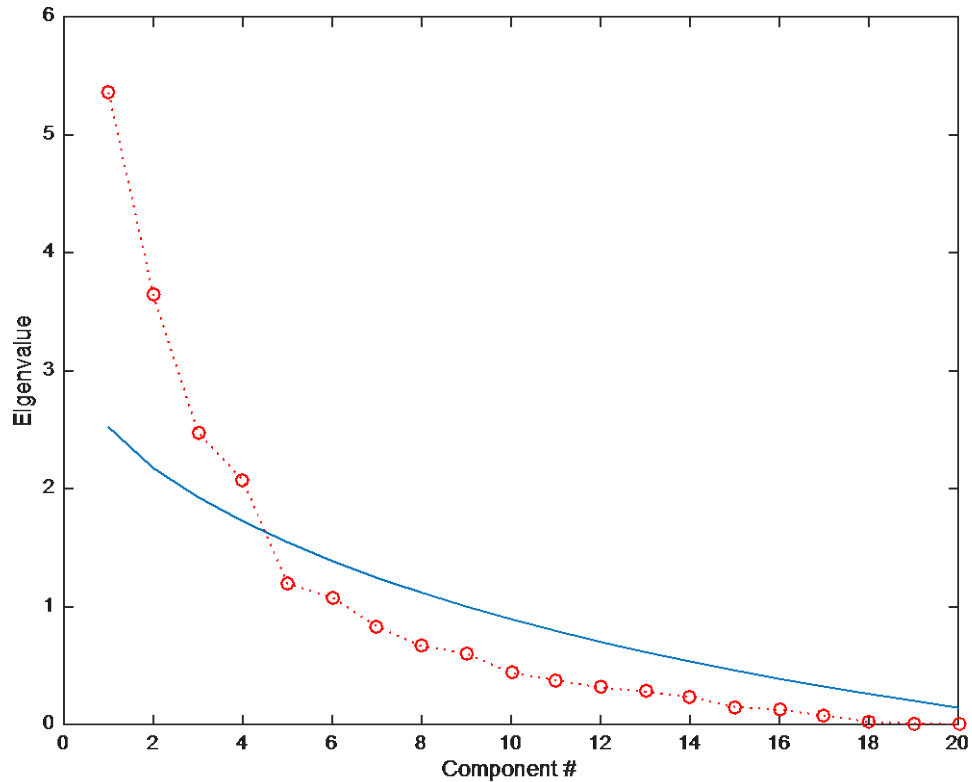


Figure 14: ICC Scree Plot

Kaiser's Criterion suggests retaining six components for the PCA and EFA. The first six components/factors explain approximately 79% of the total variance. Horn's Curve suggests retaining four components, which explain 68% of the variance. The two additional eigenvalues suggested by Kaiser's Criterion account for 11% of the variance. Cattell's Scree Test suggests keeping five components. Based on the Horn's Curve results and the knowledge that Cattell's Scree Test typically suggests keeping one more eigenvalue than necessary, the researcher retained four components for the remaining analysis.

PCA

Retaining the four components bolded in Table 14, the researcher performed PCA on the ICC variables. Table 15 shows the PCA loadings matrix.

Table 15: ICC PCA Loadings Matrix

	PC 1	PC 2	PC 3	PC 4
Permitted Air Pollutants	<u>0.601</u>	0.223	0.404	<u>0.574</u>
Emitted Air Pollutants	<u>-0.563</u>	<u>-0.514</u>	0.182	-0.191
Water Quantity Supply	0.136	0.336	-0.279	0.076
Water Quantity Demand	<u>-0.637</u>	-0.291	0.278	0.130
WW Discharge Capacity	<u>0.583</u>	0.282	-0.493	0.019
WW Discharge Demand	<u>-0.524</u>	-0.102	<u>0.604</u>	-0.145
Electrical Power Supply	<u>0.734</u>	0.194	0.070	-0.055
Electrical Power Demand	<u>-0.801</u>	-0.427	0.090	0.070
Admin Facility Inventory	<u>0.588</u>	0.345	0.313	<u>-0.513</u>
Admin Facility Occupied	<u>-0.599</u>	-0.355	-0.315	0.489
Total Base Area	0.424	-0.134	<u>0.580</u>	<u>0.629</u>
Developed/Constrained Area	-0.461	0.310	-0.434	<u>-0.554</u>
Total Dorm Rooms	0.432	<u>-0.651</u>	-0.200	-0.170
Occupied Dorm Rooms	-0.450	<u>0.684</u>	0.150	0.130
Runway Dimensions	0.482	-0.178	-0.422	0.346
Required Runway Area	-0.263	<u>0.595</u>	0.461	-0.130
Apron Dimensions	<u>0.529</u>	<u>-0.605</u>	0.187	-0.099
Required Apron Area	-0.079	<u>0.685</u>	0.280	-0.008
MX Hangar Area	0.402	-0.371	0.387	-0.361
Required MX Hangar Area	-0.476	0.457	-0.265	0.358
Eigenvalue	5.359	3.640	2.480	2.073

Components loadings with an absolute value greater than 0.5 are bolded and underlined. Six variables exhibit heavy cross loading, while four variables do not load significantly onto any components. Because of this, the components cannot easily be interpreted.

The researcher calculated the component scores for the ICC analysis. Figures 15, 16, and 17 show the score plots of the first component compared to the three other components. As seen in the supply variable analysis, total workforce serves as a differentiator between the central cluster and the outliers. Also, a few bases score similar to the large workforce bases, but do not have large workforces.

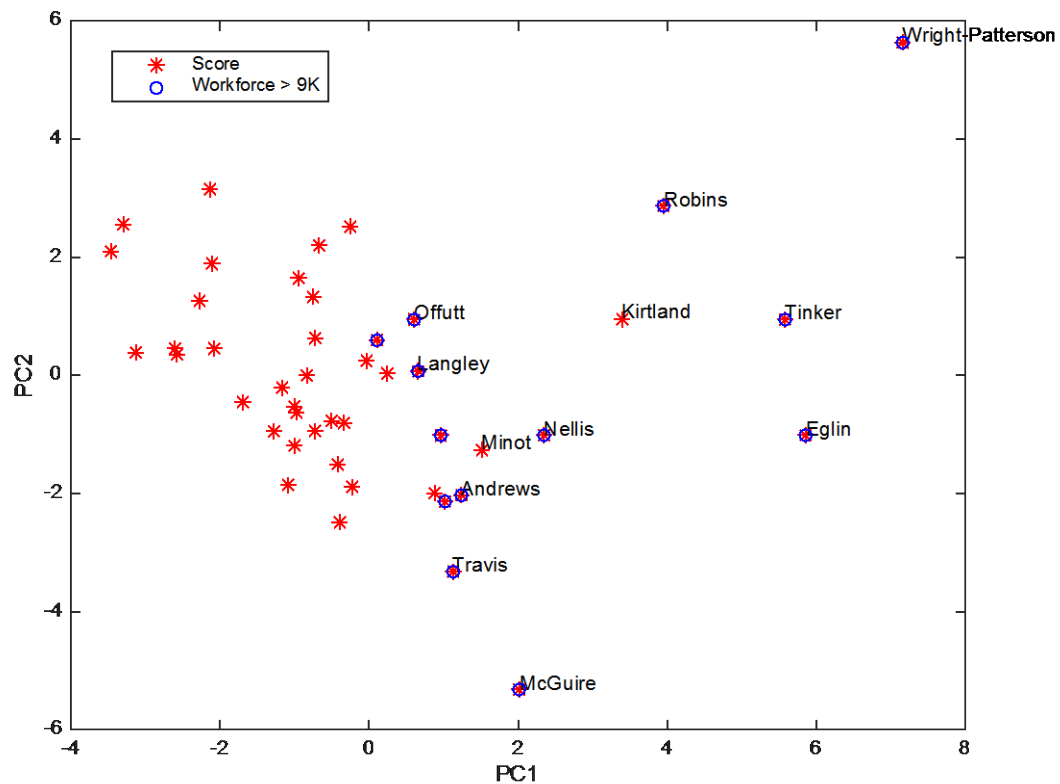


Figure 15: ICC PCA Score Plot 1

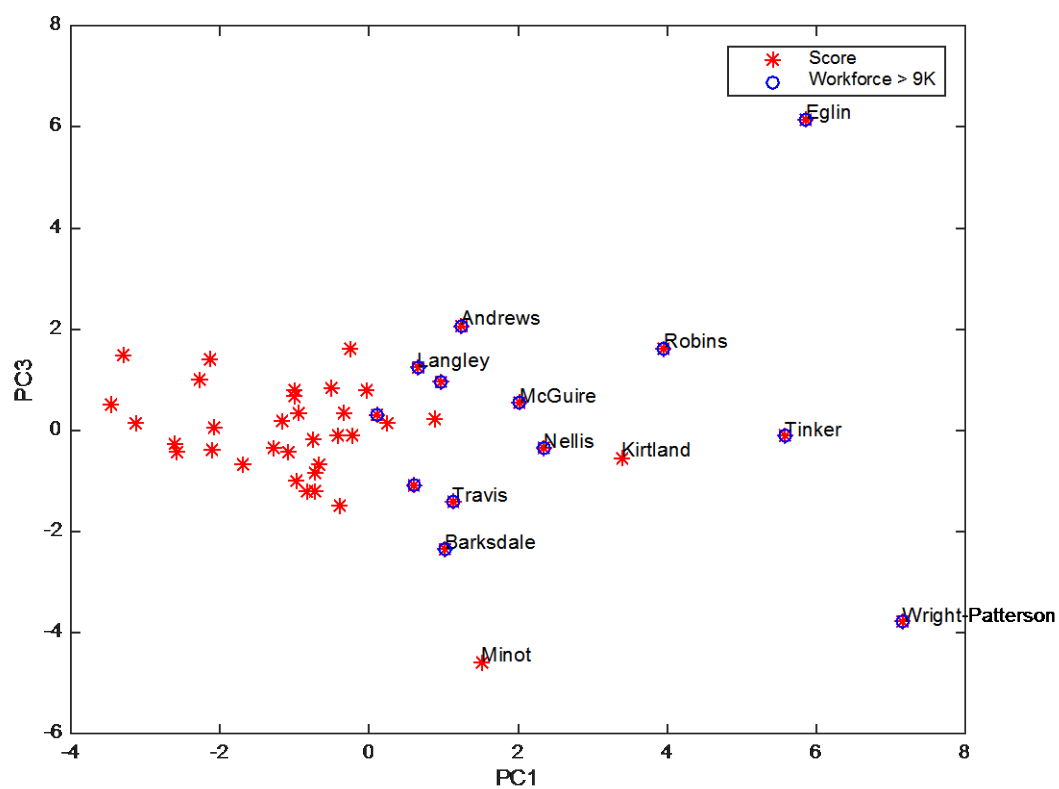


Figure 16: ICC PCA Score Plot 2

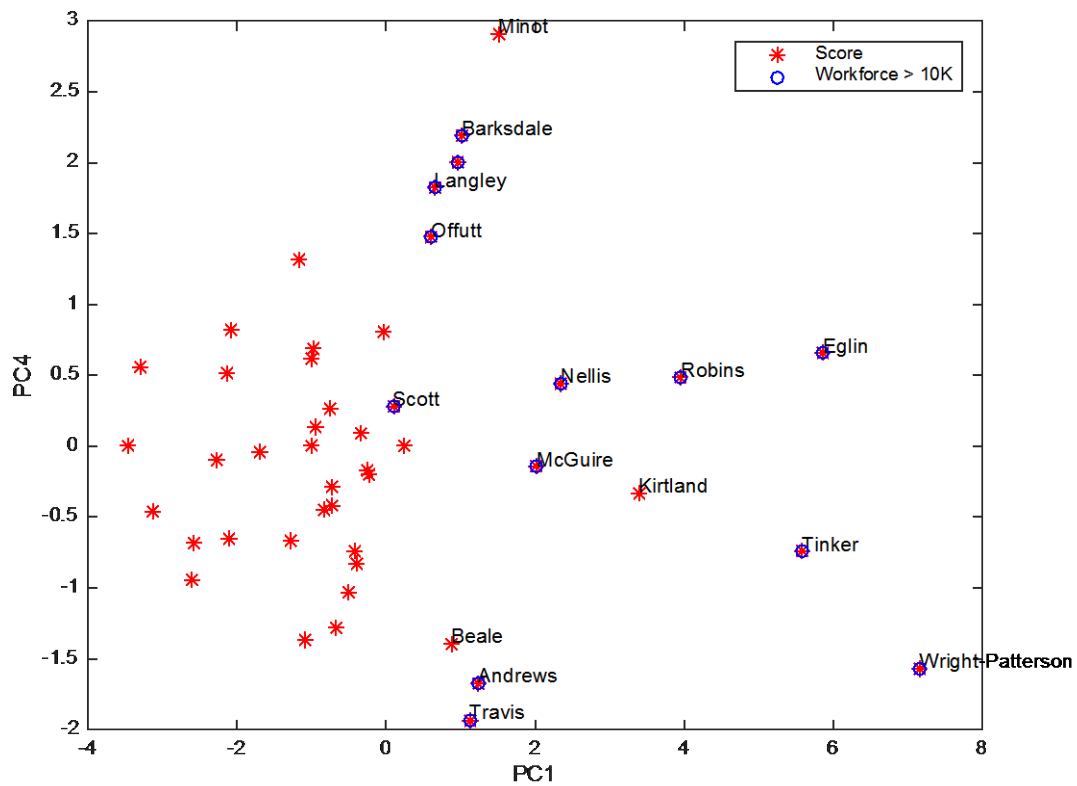


Figure 17: ICC PCA Score Plot 3

EFA

Based on the results of the dimensionality assessment, four factors were retained for the EFA. Table 16 shows the un-rotated factor loadings matrix for the ICC variables.

Table 16: ICC EFA Un-Rotated Factor Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>0.601</u>	0.223	0.404	<u>0.574</u>	0.904
Emitted Air Pollutants	<u>-0.563</u>	<u>-0.514</u>	0.182	-0.191	0.651
Water Quantity Supply	0.136	0.336	-0.279	0.076	0.215
Water Quantity Demand	<u>-0.637</u>	-0.291	0.278	0.130	0.584
WW Discharge Capacity	<u>0.583</u>	0.282	-0.493	0.019	0.663
WW Discharge Demand	<u>-0.524</u>	-0.102	<u>0.604</u>	-0.145	0.671
Electrical Power Supply	<u>0.734</u>	0.194	0.070	-0.055	0.585
Electrical Power Demand	<u>-0.801</u>	-0.427	0.090	0.070	0.837
Admin Facility Inventory	<u>0.588</u>	0.345	0.313	<u>-0.513</u>	0.825
Admin Facility Occupied	<u>-0.599</u>	-0.355	-0.315	0.489	0.824
Total Base Area	0.424	-0.134	<u>0.580</u>	<u>0.629</u>	0.929
Developed/Constrained Area	-0.461	0.310	-0.434	<u>-0.554</u>	0.805
Total Dorm Rooms	0.432	<u>-0.651</u>	-0.200	-0.170	0.680
Occupied Dorm Rooms	-0.450	<u>0.684</u>	0.150	0.130	0.710
Runway Dimensions	0.482	-0.178	-0.422	0.346	0.561
Required Runway Area	-0.263	<u>0.595</u>	0.461	-0.130	0.652
Apron Dimensions	<u>0.529</u>	<u>-0.605</u>	0.187	-0.099	0.691
Required Apron Area	-0.079	<u>0.685</u>	0.280	-0.008	0.554
MX Hangar Area	0.402	-0.371	0.387	-0.361	0.579
Required MX Hangar Area	-0.476	0.457	-0.265	0.358	0.633
Eigenvalue	5.359	3.640	2.480	2.073	13.553

As seen in the PCA loadings, several variables load heavily onto multiple factors, while some do not load onto any factors. Table 17 presents the rotated factor loadings.

Table 17: ICC EFA Rotated Loadings

Kaiser's IFS = 0.64	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	0.181	0.139	-0.317	<u>0.867</u>	0.904
Emitted Air Pollutants	-0.188	-0.211	<u>0.720</u>	-0.229	0.651
Water Quantity Supply	-0.048	0.180	-0.419	-0.071	0.215
Water Quantity Demand	-0.351	0.079	<u>0.674</u>	0.006	0.584
WW Discharge Capacity	0.118	-0.102	<u>-0.798</u>	-0.040	0.663
WW Discharge Demand	0.086	0.250	<u>0.775</u>	0.020	0.671
Electrical Power Supply	<u>0.503</u>	-0.104	-0.487	0.289	0.585
Electrical Power Demand	<u>-0.517</u>	-0.032	<u>0.727</u>	-0.199	0.837
Admin Facility Inventory	<u>0.874</u>	0.091	-0.229	0.022	0.825
Admin Facility Occupied	<u>-0.868</u>	-0.099	0.244	-0.044	0.824
Total Base Area	0.065	-0.053	0.050	<u>0.959</u>	0.929
Developed/Constrained Area	-0.031	0.269	-0.024	<u>-0.855</u>	0.805
Total Dorm Rooms	0.125	<u>-0.811</u>	-0.083	0.000	0.680
Occupied Dorm Rooms	-0.125	<u>0.829</u>	0.055	-0.067	0.710
Runway Dimensions	-0.208	-0.407	<u>-0.548</u>	0.229	0.561
Required Runway Area	0.281	<u>0.725</u>	0.218	0.004	0.652
Apron Dimensions	0.325	<u>-0.700</u>	0.068	0.301	0.691
Required Apron Area	0.230	<u>0.702</u>	-0.071	0.060	0.554
MX Hangar Area	<u>0.572</u>	-0.427	0.216	0.153	0.579
Required MX Hangar Area	<u>-0.534</u>	<u>0.562</u>	-0.131	-0.125	0.633
Eigenvalue	3.181	3.796	3.799	2.777	13.553

The rotated loadings aid with interpreting the factors, but do not eliminate the issues seen in the un-rotated solution. Two variables load heavily onto multiple factors and one variable does not load above 0.5 on any factor. However, the rotation groups the

variables into a structure that can be interpreted. Factor 1 appears to represent workplace facilities. Factor 2 appears to represent dorms and airfield pavements. Factor 3 primarily contains variables that reflect utility systems. Finally, factor 4 represents natural infrastructure. These groupings match the groupings discovered in the supply variable EFA. As seen in the supply variable analysis, the factor score plots shown in Figures 18, 19, and 20 provide a visual representation that can be used to compare installations and identify the specific capacity strengths and weaknesses at each installation. The complete set of score plots is located in Appendix E.

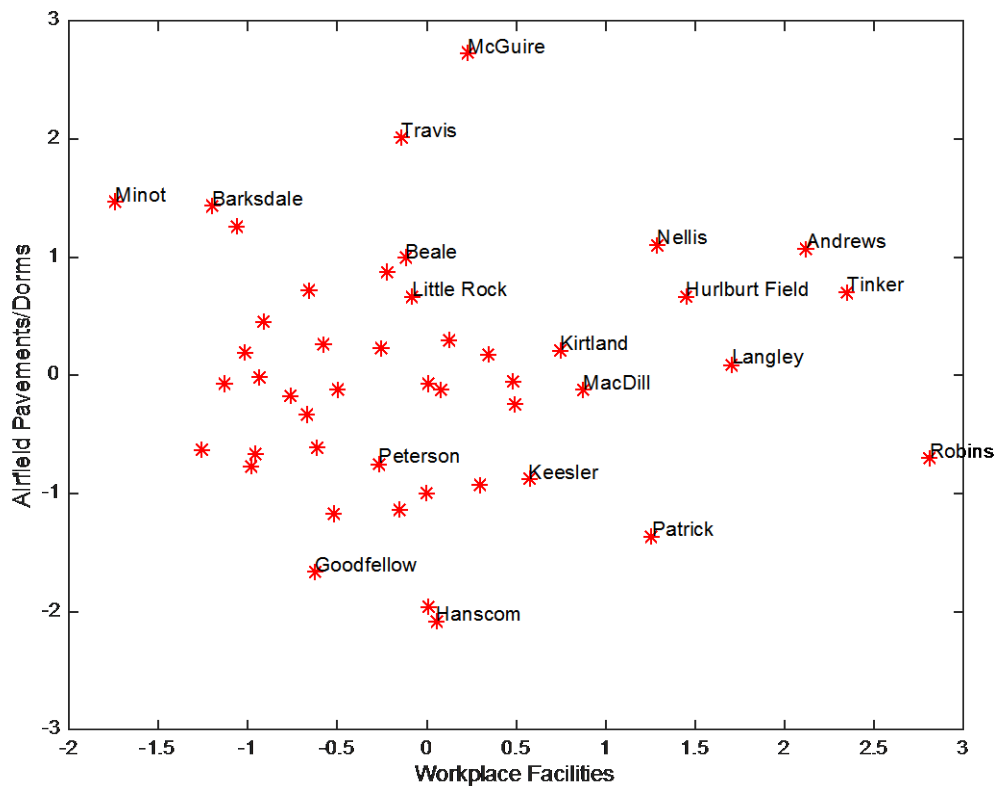


Figure 18: ICC EFA Score Plot 1

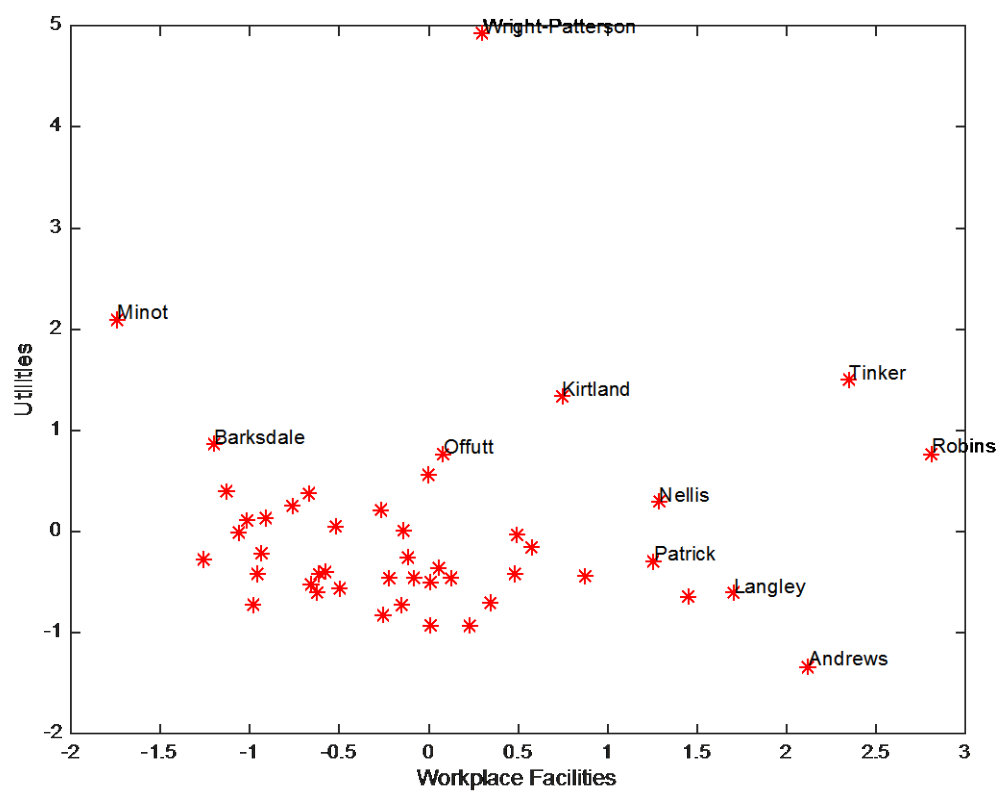


Figure 19: ICC EFA Score Plot 2

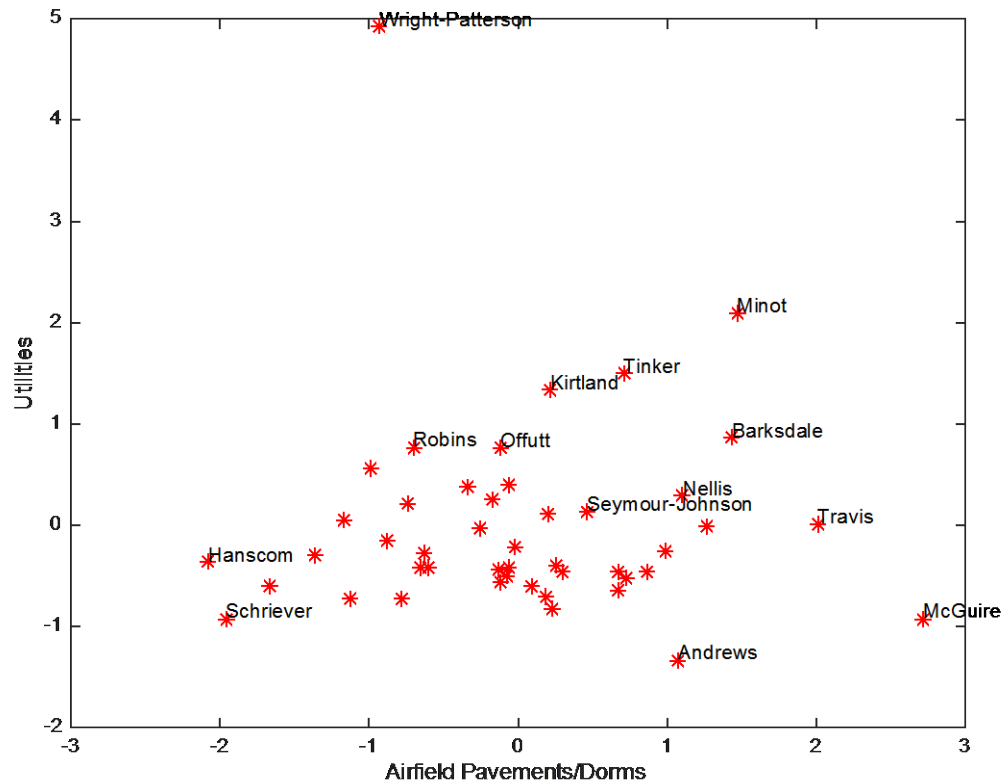


Figure 20: ICC EFA Score Plot 3

The ICC is calculated by combining the weighted factor scores of each installation. Table 18 lists the weights of each factor. Factors 2 and 4, which represent airfield pavements/dormitories and utility systems, are the highest weighted factors and have equal weights. However, the other two factor's weights are relatively close. Each factor contributes roughly 25% to the ICC.

Table 18: ICC Factor Weights

Factor	Classification	Weight
1	"Workplace Facilities"	23.5%
2	"Airfield Pavements/Dorms"	28.0%
3	"Utility Systems"	28.0%
4	"Natural Infrastructure"	20.5%

The individual factor scores and composite scores for each installation are listed in Table 19. The scores listed in the table are the raw factor scores, not the weighted factor scores. Therefore, simply adding the factor scores listed in Table 19 will not produce the ICC. Instead, the following formula should be applied:

$$ICC = 0.235(factor\ 1\ score) + 0.280(factor\ 2\ score) + 0.280(factor\ 3\ score) + .205(factor\ 4\ score) \quad (16)$$

The installations are sorted in descending order based on the ICC score. The scores range from a maximum value of 1.3 to a minimum value of -0.85.

Table 19: Factor and ICC Scores

<u>Installation</u>	<u>Workplace Facilities</u>	<u>Airfield Pavements/Dorms</u>	<u>Utilities</u>	<u>Natural Infrastructure</u>	<u>ICC</u>
Wright-Patterson	0.303	-0.928	4.921	0.546	1.303
Eglin	0.479	-0.060	-0.413	6.144	1.239
Tinker	2.351	0.708	1.500	-0.154	1.139
McGuire	0.230	2.721	-0.919	0.645	0.690
Kirtland	0.747	0.216	1.336	0.356	0.683
Robins	2.813	-0.705	0.774	-0.036	0.672
Nellis	1.290	1.106	0.291	-0.694	0.552
Minot	-1.739	1.467	2.097	-0.682	0.451
Travis	-0.139	2.011	0.012	-0.550	0.421
Barksdale	-1.199	1.437	0.859	-0.015	0.359
Andrews	2.124	1.075	-1.330	-0.482	0.328
Beale	-0.121	0.989	-0.253	0.520	0.284
Hurlburt	1.451	0.666	-0.634	-0.564	0.234
Langley	1.704	0.094	-0.610	-0.709	0.110
Offutt	0.083	-0.120	0.769	-0.512	0.097
Dyess	-1.063	1.262	-0.007	-0.186	0.064
Holloman	-0.761	-0.170	0.249	1.033	0.055
Davis	-0.225	0.866	-0.460	-0.062	0.048
Monthan	-0.080	0.669	-0.463	-0.250	-0.012

Scott	0.491	-0.251	-0.039	-0.247	-0.017
MacDill	0.877	-0.124	-0.431	-0.402	-0.032
Whiteman	0.129	0.294	-0.461	-0.091	-0.035
Cannon	0.347	0.182	-0.710	-0.075	-0.082
Seymour-Johnson	-0.911	0.463	0.139	-0.217	-0.090
Dover	-0.663	0.720	-0.516	-0.151	-0.130
Ellsworth	-1.011	0.201	0.103	-0.039	-0.160
Mountain Home	-1.136	-0.063	0.404	0.049	-0.161
Moody	-0.249	0.228	-0.821	0.290	-0.165
Sheppard	-0.667	-0.338	0.371	-0.116	-0.171
Tyndall	-0.492	-0.115	-0.554	0.542	-0.192
Patrick	1.260	-1.365	-0.288	-0.187	-0.205
Altus	-0.576	0.255	-0.400	-0.222	-0.221
Peterson	-0.267	-0.745	0.211	-0.071	-0.227
Shaw	0.008	-0.076	-0.503	-0.397	-0.242
Maxwell	0.001	-0.993	0.558	-0.604	-0.245
Keesler	0.571	-0.877	-0.155	-0.660	-0.290
Luke	-0.931	-0.023	-0.218	-0.207	-0.328
Malmstrom	-0.607	-0.605	-0.424	-0.179	-0.468
FE Warren	-0.519	-1.172	0.046	-0.497	-0.539
Columbus	-1.259	-0.625	-0.283	-0.028	-0.556
Buckley	-0.156	-1.132	-0.716	-0.041	-0.563
Laughlin	-0.956	-0.661	-0.411	-0.241	-0.574
Hanscom	0.053	-2.076	-0.365	0.203	-0.630
Vance	-0.977	-0.778	-0.727	-0.179	-0.687
Goodfellow	-0.625	-1.665	-0.605	-0.340	-0.852
Schriever	0.015	-1.961	-0.920	-0.242	-0.853

Figure 21 shows the distribution of ICC scores. The scores appear to follow a normal distribution, but do not pass the Kolmogorov–Smirnov test for normality. If the distribution was normal, the ICC could be divided into score categories based on standard deviations. However, this research establishes score thresholds based on natural breaks in the distribution. These thresholds create three score divisions: high capacity, medium capacity, and low capacity. The high capacity category includes bases with ICC score greater than 0.25. The medium capacity category includes bases with ICC scores less than 0.25 and greater than -0.35. The low capacity category includes bases with ICC scores less than -0.35.

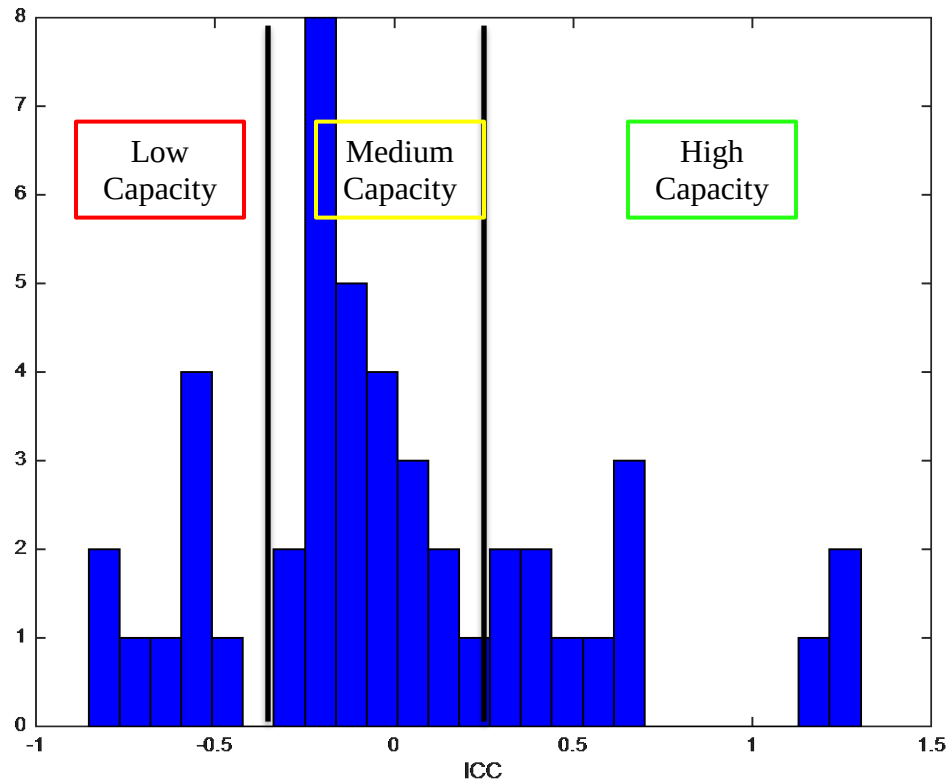
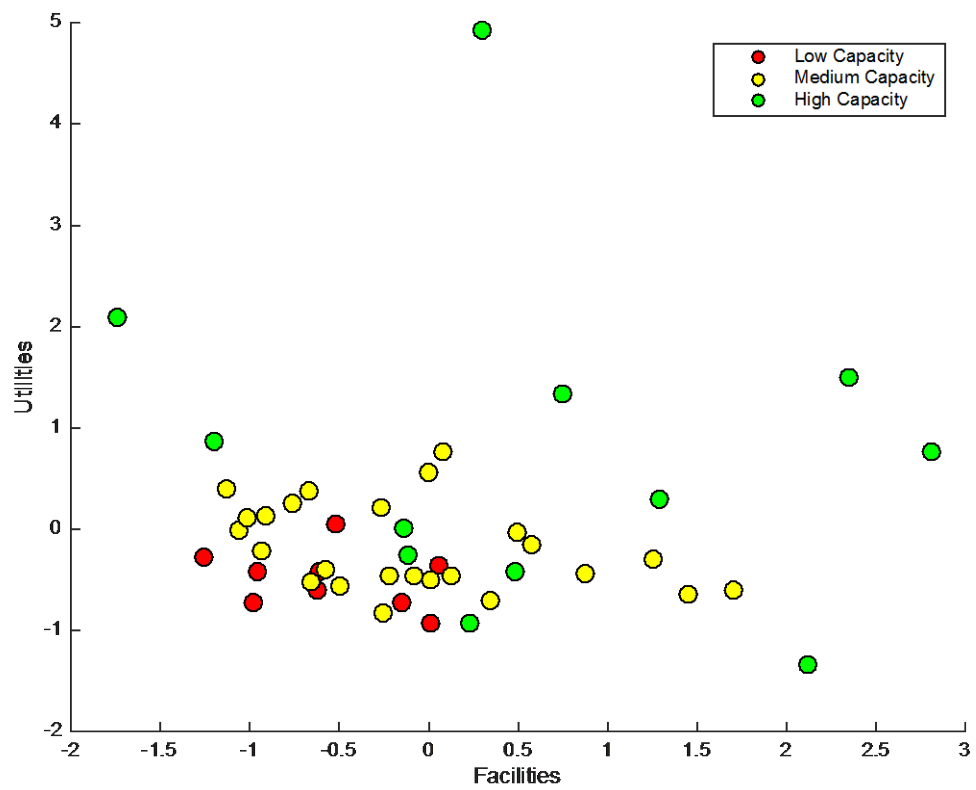


Figure 21: ICC Score Distribution

Figures 22 and 23 show a sample of the ICC EFA score plots with the score classifications. In Figure 22, the high, medium, and low capacities appear to mix and no clear distinction exists. This plot indicates that although a base may be classified as high capacity, that base may have average to low capacity in certain areas. In addition, this plot shows that the utilities and facilities factors do not distinguish what is a high, medium, or low capacity base. However, Figure 23 provides more distinct groupings of capacity.



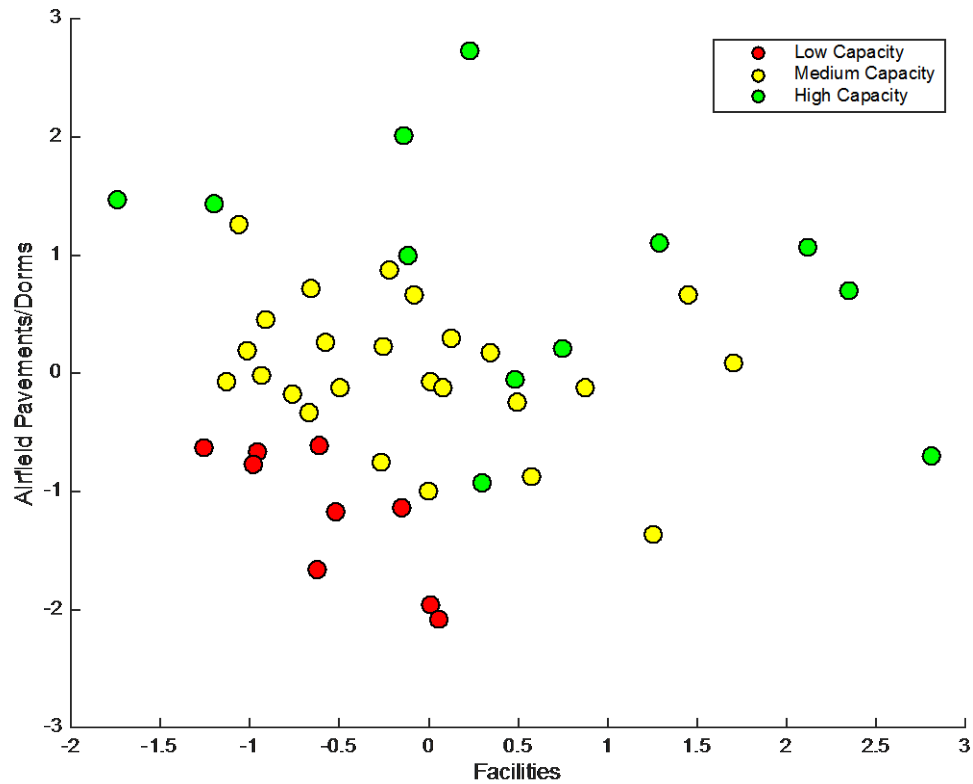


Figure 23: ICC EFA Classification Score Plot 2

Plotting the classifications with the ICC PCA score produces slightly different results. Figure 24 shows the score plot, classified by ICC score, of the first and second principal components. In this plot, the installations form distinct groups based on the ICC scores calculated.

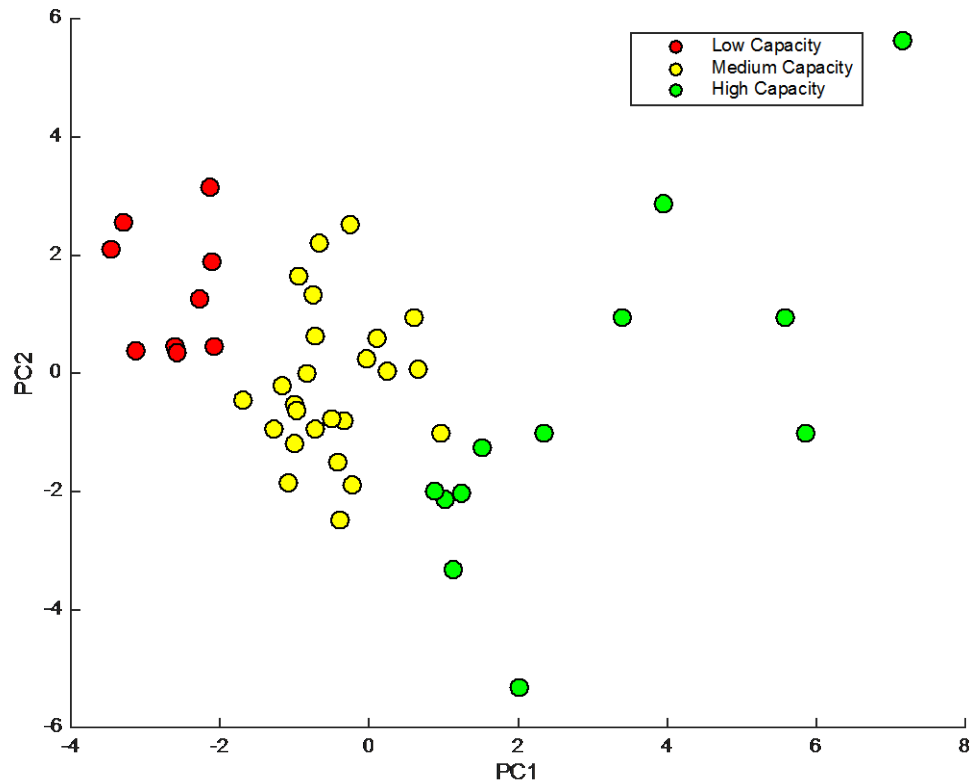


Figure 24: ICC PCA Classification Score Plot

Using the rotated factor loading results, this research estimated the weights of each variable. These weights are shown in Table 20. These weights were not used to calculate the ICC, however, the information can be used to identify the degree to which variables contribute to the ICC. These estimated weights show that the administrative facility and base area variables contribute highly to the ICC score.

Table 20: Individual Variable Weights

<u>Variable</u>	<u>Weight</u>
Permitted Air Pollutants	6.93%
Emitted Air Pollutants	4.78%
Water Quantity Supply	1.62%
Water Quantity Demand	4.19%
WW Discharge Capacity	5.87%
WW Discharge Demand	5.54%
Electrical Power Supply	2.33%
Electrical Power Demand	4.88%
Admin Facility Inventory	7.04%
Admin Facility Occupied	6.94%
Total Base Area	8.47%
Developed/Constrained Area	6.73%
Total Dorm Rooms	6.06%
Occupied Dorm Rooms	6.33%
Runway Dimensions	2.77%
Required Runway Area	4.84%
Apron Dimensions	4.52%
Required Apron Area	4.54%
MX Hangar Area	3.01%
Required MX Hangar Area	2.63%

Summary

This chapter presented the results of the outlier analysis, dimensionality assessment, PCA and EFA for several sets of variables. These sets were based on different transformations of the data (supply only, demand only, supply-demand ratio,

excess capacity, and the total dataset) and led to some insights as well as inconclusive analysis. The inconclusive analysis results are presented in the appendices. Also, this chapter presented individual factor scores and ICC scores for each installation. The following chapter provides an interpretation of these results and a research conclusion.

V. Discussion and Conclusion

Chapter Overview

This chapter provides an interpretation and discussion of the results presented in the previous chapter. Specifically, the chapter draws conclusions from each analysis performed and highlights how the methods and results can be used by the United States Air Force. This chapter also reviews the research questions presented in Chapter 1 to provide an assessment for whether or not the research objectives for the study were met. The chapter closes with a discussion on the limitations of this study, specifically data, quality, as well as presenting potential ideas for future research.

Discussion: Supply Variables

As stated in the previous chapter, the supply variables represent the total infrastructure capacity at each installation, regardless of the current demand or load. The results of the supply variable PCA offer some understanding about the nature of CONUS installation capacity. While the PCA loadings do not provide any insight, the score plots can be used to identify potential bases that have excess capacity, based on the total workforce. Figure 25 shows the score plot of the first and third principal components. In this figure, the points designated with a blue circle represent bases that have a workforce greater than 9,000. These bases appear to form a cluster, while the bases with workforces less than 9,000 cluster together as well. However, Minot, Kirtland, and Beale Air Force Bases score in the same area as the large workforce bases. This observation indicates that these three installations have the same characteristics as large workforce bases, but are not classified as having a large workforce. In the context of strategic basing, these installations appear to maintain excess capacity, making the bases potential candidates to accept additional personnel and mission assets. However, the plot does not identify the

specific areas of excess capacity that exist. The EFA results provide further insight about the specific areas of capacity at each installation.

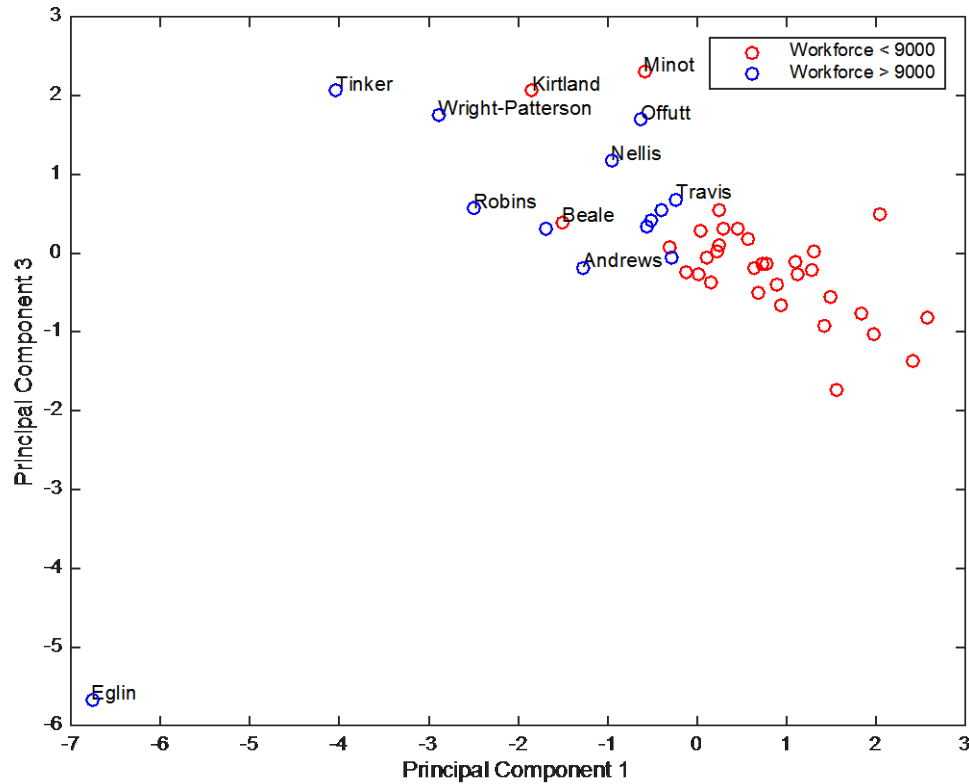


Figure 25: Supply Variable PCA Score Plot 2

The rotation of the factors that occurs in EFA provides the researcher with a different “perspective” of the data that is easier to interpret. Table 21 shows the rotated supply variable loadings. The structure of the loading matrix confirms that four common factors exist in this data. The variables also appear to form more logical groupings. Water quantity, wastewater discharge capacity, and electrical power supply load heavily into the first factor. Factor 1 can be interpreted as representing traditional utility systems. In the second factor, dormitory rooms, runway dimensions, and apron dimensions all load above 0.5, so Factor 2 represents airfield pavements and dormitories. Permitted air

pollutants and total base area load heavily onto factor 3, meaning that factor may represent natural infrastructure. Finally, administrative facility space and maintenance hangar space load heavily onto factor 4. This factor represents workplace facilities. With this interpretation, the researcher has the ability to identify specific areas of high and low capacity at each installation.

Table 21: Supply Variable EFA Rotated Factor Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	-0.196	-0.026	<u>-0.939</u>	0.130	0.937
Water Quantity	<u>-0.524</u>	-0.238	0.021	-0.102	0.341
WW Discharge	<u>-0.829</u>	0.142	0.006	0.136	0.726
Electrical Power Supply	<u>-0.578</u>	0.294	-0.349	0.385	0.690
Admin Facility Space	-0.297	0.028	-0.149	<u>0.793</u>	0.741
Total Base Area	0.119	0.113	<u>-0.937</u>	0.042	0.907
Total Dorm Rooms	-0.077	<u>0.726</u>	0.121	0.097	0.557
Runway Dimensions	-0.408	<u>0.584</u>	-0.248	-0.452	0.774
Apron Dimensions	0.142	<u>0.847</u>	-0.231	0.185	0.824
MX Hangar Area	0.263	0.450	-0.072	<u>0.644</u>	0.692
Eigenvalue	1.698	1.964	2.039	1.488	7.189

The EFA score plots provide a method to visually examine the specific areas that contribute to installation capacity, as well as a means to easily compare installations. Figure 26 shows the EFA score plot of the utilities and workplace facilities factors. This plot can be used as a tool for planners and analysts to gain understanding about installation capacity. For example, Joint Base Andrews scores high on the workplace facilities factor, meaning the base has a relatively large inventory of administrative and hangar facilities. However, the base's utility score is one of the lowest, meaning JB Andrew's utility systems have a much smaller capacity compared to the other bases. In

the context of major basing decision, this observation may indicate that JB Andrews maintains the facilities to accept a new mission, but would probably need significant utility upgrades. However, this observation serves as one example. Many other installations exhibit similar characteristics: high capacity in one area and low capacity in another. The results show that no base has the largest capacity in every factor. Some of the largest bases such as Wright-Patterson AFB, JB McGuire, and Tinker AFB all have at least one factor of capacity that is below average. The rotated score plots also provide further insight to build upon the PCA results.

In the PCA score plots, Kirtland, Minot, and Beale Air Force Bases scored similar to large workforce bases, but did not have a large workforce. However, those plots did not provide information about why these bases scored similar to large bases, or what

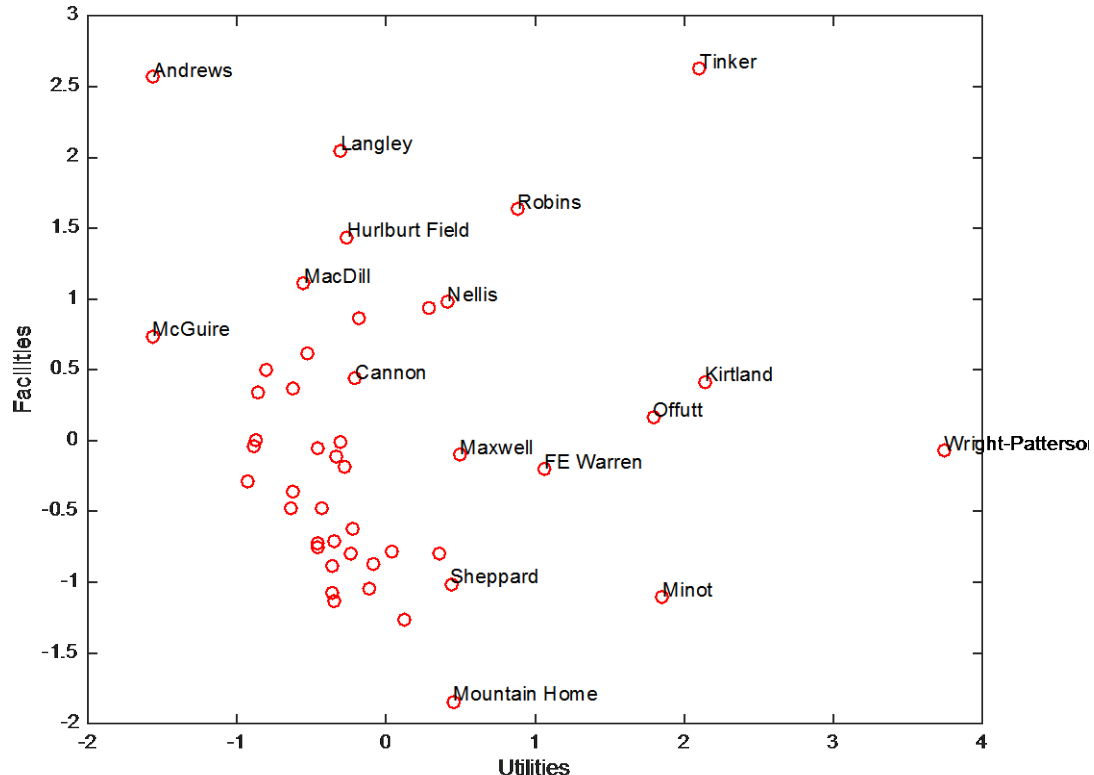


Figure 26: Supply Variable EFA Score Plot 2

factors contributed to the higher scores. However, the EFA score plots offer an explanation as to why these three bases have high capacity scores. Figure 27 compares the utility scores with the airfield pavements and dormitories scores. Kirtland AFB and Minot AFB score relatively high in the utility factor, while Beale scores high in the airfield pavements/dormitories factor. However, Figure 26 shows none of the three bases scoring relatively high in the facilities factor. In conclusion, these three bases ranked similar to the large workforce bases in the PCA analysis, but no information was provided as to why. The EFA results show this ranking is a product of the installations' high utility and airfield pavements/dormitories scores.

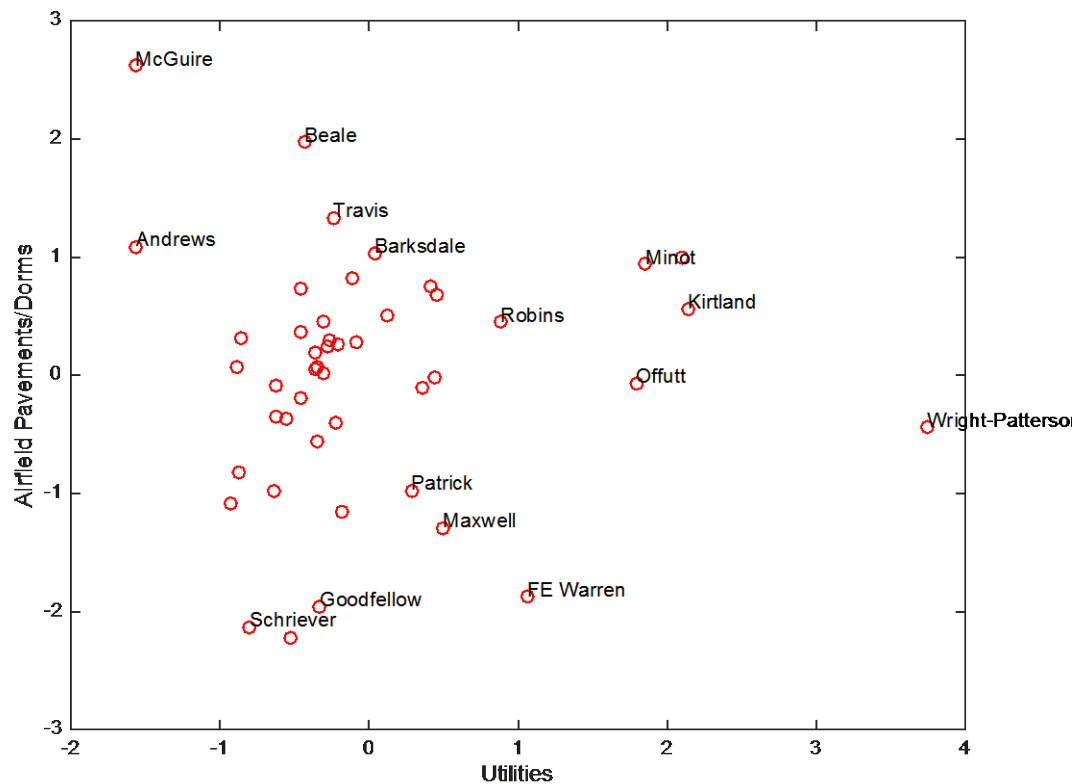


Figure 27: Supply Variable EFA Score Plot 1

Discussion: Inconclusive Analysis

Of the variables analyzed, this research characterized three configurations as inconclusive. Those configurations included the demand variables, the demand-capacity ratios, and excess capacity. The multivariate analysis methods succeeded in reducing the dimensionality of the data sets, however the objective of this research is to identify underlying factors in capacity data. The results of these configurations provide no insight to the research objectives or questions because of the lack of interpretability in the loadings structure. Despite this, this research includes the results of each analysis in Appendices B, C, and D.

Discussion: Installation Composite Capacity

This portion of the analysis used both the supply and demand indicators as independent variables. By using these variables, the results provide an even greater understanding about capacity by considering both the limits of capacity at each installation, as well as the current demand. Although this analysis utilized an additional ten variables, the results produced align closely to what was found in the supply analysis. This section reviews and discusses the PCA results, EFA results, and finally the ICC scores.

Similar to the supply analysis, the ICC PCA loadings offer limited insight to the specific characteristics of installation capacity. Although the loadings provide no insight to capacity, the score plots of the PCA loadings, however, can be used as a tool to compare bases. Figure 28 shows the plot of the first and fourth principal component, PC1 and PC4, respectively. The bases with large workforces score around a central

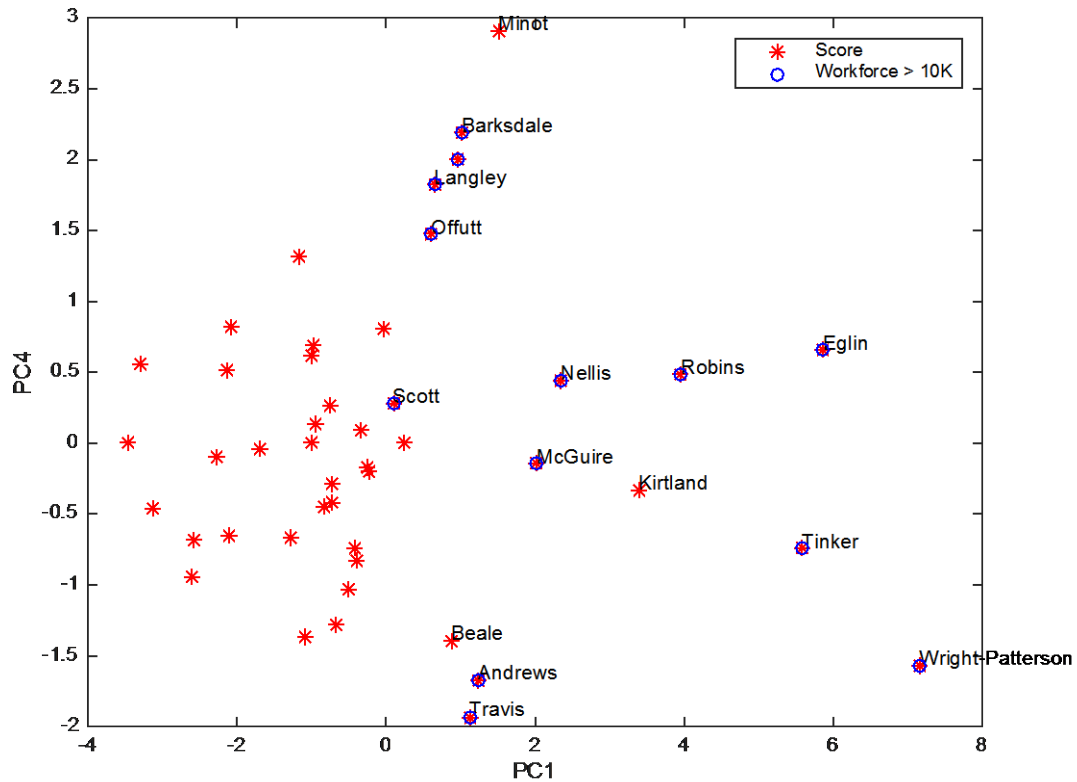


Figure 28: ICC PCA Score Plot 3

cluster of smaller bases. Once again, Kirtland, Beale, and Minot Air Force Bases locate in the same area as the large workforce bases. This observation matches what was produced in the supply analysis. The reasons for these bases scoring similar to the large workforce base are the high utility and airfield pavement/dormitory capacities. Despite this, both analyses show that Minot, Kirtland, and Beale Air Force Bases maintain above average capacities and should be considered as potential candidates to accept addition missions.

The factor rotation in the EFA resolves several issues found in the un-rotated factor solutions and provides the researcher with a solution that can be interpreted. However, the rotated loadings produced in this analysis lack the precision seen in the supply analysis. These loadings are not as “clean” as previously seen, which means the

researcher's interpretation contains greater subjective judgment. Table 22 shows the rotated factor loadings for the 20 variables included in this analysis.

In general, the factors discovered in this analysis align with the factors seen in the supply analysis. Factor 1 appears to represent workplace facilities. Factor 2 represents dorms and airfield pavements. Factor 3 primarily contains variables that reflect utility systems. Finally, factor 4 represents natural infrastructure. Although each factor represents an underlying construct, instances exist where other variables load heavily in a

Table 22: ICC EFA Rotated Factor Loadings

Kaiser's IFS = 0.64	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	0.181	0.139	-0.317	<u>0.867</u>	0.904
Emitted Air Pollutants	-0.188	-0.211	0.720	-0.229	0.651
Water Quantity Supply	-0.048	0.180	-0.419	-0.071	0.215
Water Quantity Demand	-0.351	0.079	<u>0.674</u>	0.006	0.584
WW Discharge Capacity	0.118	-0.102	<u>-0.798</u>	-0.040	0.663
WW Discharge Demand	0.086	0.250	<u>0.775</u>	0.020	0.671
Electrical Power Supply	0.503	-0.104	-0.487	0.289	0.585
Electrical Power Demand	-0.517	-0.032	<u>0.727</u>	-0.199	0.837
Admin Facility Inventory	<u>0.874</u>	0.091	-0.229	0.022	0.825
Admin Facility Occupied	<u>-0.868</u>	-0.099	0.244	-0.044	0.824
Total Base Area	0.065	-0.053	0.050	<u>0.959</u>	0.929
Developed/Constrained Area	-0.031	0.269	-0.024	<u>-0.855</u>	0.805
Total Dorm Rooms	0.125	<u>-0.811</u>	-0.083	0.000	0.680
Occupied Dorm Rooms	-0.125	<u>0.829</u>	0.055	-0.067	0.710
Runway Dimensions	-0.208	-0.407	-0.548	0.229	0.561
Required Runway Area	0.281	<u>0.725</u>	0.218	0.004	0.652
Apron Dimensions	0.325	<u>-0.700</u>	0.068	0.301	0.691
Required Apron Area	0.230	<u>0.702</u>	-0.071	0.060	0.554
MX Hangar Area	<u>0.572</u>	-0.427	0.216	0.153	0.579
Required MX Hangar Area	<u>-0.534</u>	0.562	-0.131	-0.125	0.633
Eigenvalue	3.181	3.796	3.799	2.777	13.553

factor. For example, the variables in factor 2 that have higher loadings are primarily dormitory and airfield pavement variables, but the required maintenance hangar variable also loads above 0.5 in that factor. However, the researcher interpreted the factors in general terms, with the understanding that the factors are slightly influenced by variables not consistent with the name given to that factor. The highlighted values in Table 22 designate a variable loading that is inconsistent with the general theme of each factor. Also, the researcher relaxed the threshold of 0.5 for the loadings in this scenario, as it is only a heuristic. Considering all of these issues, the variables appear to form the same factors found in the supply analysis, albeit with a few deviations.

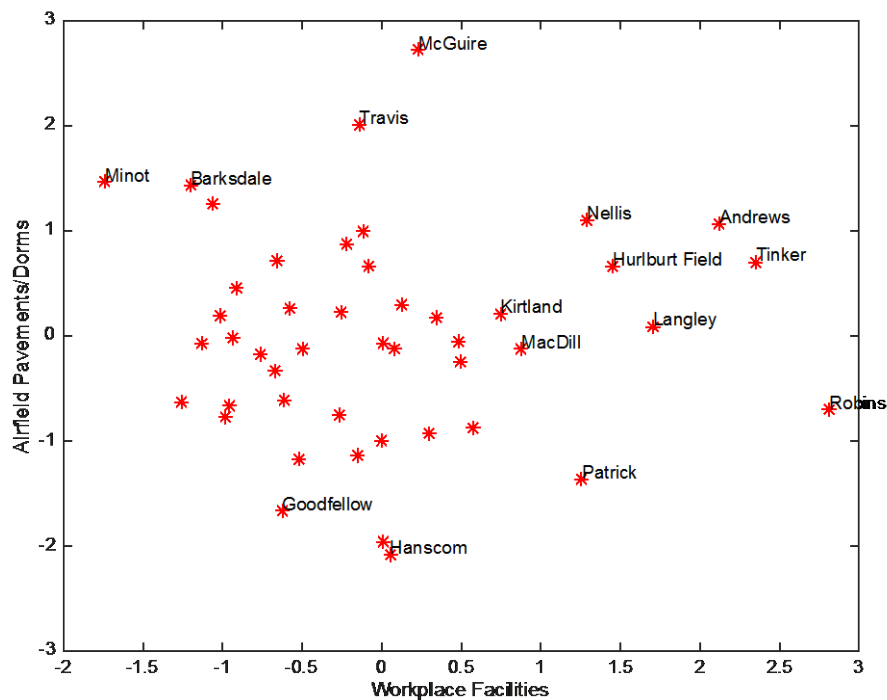


Figure 29: ICC EFA Score Plot 1

The Air Force can use the score plots in the same manner as described before, except now the score plots reflect demand at each installation. The scores in these plots

reflect the magnitude of capacity at each base, relative to the whole set of bases. Because of the min-max normalization, a high value in a supply variable increases the score, while a high value in a demand variable, weakens the score. Figure 29 shows an example of a score plot produced in this portion of the analysis.

The score plots provide not only a tool to visual simplified capacity data, but also a tool to support strategic basing decisions. For example, consider a situation where the Air Force planned on relocating an undergraduate pilot training (UPT) organization. Planners could use the information they know about UPT squadrons and these score plots to identify an appropriate installation to support the incoming mission. The analysts may know that a UPT squadron does not need a significant amount of administrative space, but it does require a large amount of airfield pavements. The analysts can use the score plot in Figure 29 to identify potential bases with lots of airfield pavements and adequate facility space. In this example, Travis, Barksdale, and Minot Air Force Bases would be bases to consider for the beddown of a new UPT wing, given their large amount of airfield pavement space, dormitory rooms, and adequate amount of facility space. This scenario provides a simple example of how these results can assist in the decision making process.

The final results, the ICC scores, are a product of the individual factor scores. The ICC scores, presented in Table 23, provide a single measure to evaluate and compare the installations included in this research. The ICC score reflects the “health” of an installation in terms of overall capacity. In general, the ICC scores rank the installations with the greatest capacity in terms of the four factors defined. The individual factor

scores provide information about the capacity strengths and weaknesses, with regard to each of the four factors, at each installation.

Table 23: Factor and ICC Scores

<u>Installation</u>	<u>Workplace Facilities</u>	<u>Airfield Pavements/Dorms</u>	<u>Utilities</u>	<u>Natural Infrastructure</u>	<u>ICC</u>
Wright-Patterson	0.303	-0.928	4.921	0.546	1.303
Eglin	0.479	-0.060	-0.413	6.144	1.239
Tinker	2.351	0.708	1.500	-0.154	1.139
McGuire	0.230	2.721	-0.919	0.645	0.690
Kirtland	0.747	0.216	1.336	0.356	0.683
Robins	2.813	-0.705	0.774	-0.036	0.672
Nellis	1.290	1.106	0.291	-0.694	0.552
Minot	-1.739	1.467	2.097	-0.682	0.451
Travis	-0.139	2.011	0.012	-0.550	0.421
Barksdale	-1.199	1.437	0.859	-0.015	0.359
Andrews	2.124	1.075	-1.330	-0.482	0.328
Beale	-0.121	0.989	-0.253	0.520	0.284
Hurlburt Field	1.451	0.666	-0.634	-0.564	0.234
Langley	1.704	0.094	-0.610	-0.709	0.110
Offutt	0.083	-0.120	0.769	-0.512	0.097
Dyess	-1.063	1.262	-0.007	-0.186	0.064
Holloman	-0.761	-0.170	0.249	1.033	0.055
Davis	-0.225	0.866	-0.460	-0.062	0.048
Monthan	-0.080	0.669	-0.463	-0.250	-0.012
Little Rock	0.491	-0.251	-0.039	-0.247	-0.017
MacDill	0.877	-0.124	-0.431	-0.402	-0.032
Whiteman	0.129	0.294	-0.461	-0.091	-0.035
Cannon	0.347	0.182	-0.710	-0.075	-0.082
Seymour-Johnson	-0.911	0.463	0.139	-0.217	-0.090
Dover	-0.663	0.720	-0.516	-0.151	-0.130
Ellsworth	-1.011	0.201	0.103	-0.039	-0.160
Mountain Home	-1.136	-0.063	0.404	0.049	-0.161
Moody	-0.249	0.228	-0.821	0.290	-0.165
Sheppard	-0.667	-0.338	0.371	-0.116	-0.171
Tyndall	-0.492	-0.115	-0.554	0.542	-0.192
Patrick	1.260	-1.365	-0.288	-0.187	-0.205
Altus	-0.576	0.255	-0.400	-0.222	-0.221
Peterson	-0.267	-0.745	0.211	-0.071	-0.227
Shaw	0.008	-0.076	-0.503	-0.397	-0.242
Maxwell	0.001	-0.993	0.558	-0.604	-0.245
Keesler	0.571	-0.877	-0.155	-0.660	-0.290
Luke	-0.931	-0.023	-0.218	-0.207	-0.328
Malmstrom	-0.607	-0.605	-0.424	-0.179	-0.468
FE Warren	-0.519	-1.172	0.046	-0.497	-0.539
Columbus	-1.259	-0.625	-0.283	-0.028	-0.556
Buckley	-0.156	-1.132	-0.716	-0.041	-0.563
Laughlin	-0.956	-0.661	-0.411	-0.241	-0.574

Hanscom	0.053	-2.076	-0.365	0.203	-0.630
Vance	-0.977	-0.778	-0.727	-0.179	-0.687
Goodfellow	-0.625	-1.665	-0.605	-0.340	-0.852
Schriever	0.015	-1.961	-0.920	-0.242	-0.853

The ICC scores range from approximately 1.3 to -0.85. However, the negative values do not reflect that the capacity at an installation has been exceeded. The negative scores are present because the methods use standardized data to calculate factor scores. That is, the data is standardized so that the mean in each variable is equal to zero and the standard deviation is equal to one. The values of the factor scores and the ICC scores should be considered relative to the other scores. The rankings of the installations based on ICC score provide an idea about which installations have the highest capacity, relative to the other installations in the inventory and can possibly support additional personnel and additional mission assets. Those installations at the bottom of the list are found to be the least likely to be able to support an increase in workforce and new missions. Table 23 shows that Wright-Patterson, Eglin, and Tinker Air Force Bases have the highest capacity. This ranking makes logical sense, as these bases represent three of top five largest workforce bases. Also, the ICC scores drop significantly after these three bases, meaning there is a large gap in capacity between the top three bases and the rest of the Air Force. From that point, the scores gradually decrease. The five lowest scores belong to Laughlin, Hanscom, Vance, Goodfellow and Schriever Air Force Bases. These bases represent either UPT bases or bases without an airfield.

The high, medium, and low ICC score classifications provided additional insight. When plotted using these classifications, the EFA ICC score plots show that although a base may have a high or medium ICC score, that base may have average to low capacity

in one or more factors. Likewise, bases that have a low capacity classification may have above average capacity in certain factors. The plots also show how certain factors or combination of factors can distinguish between high, medium, and low ICC scores. For example, the Utilities and Facilities factor score plots showed no distinguishable differences between capacities. However, Figure 30 shows that the PCA score plot clearly distinguishes between groups, despite only accounting for 45% of the variance. This observation is surprisingly because the scores were created several steps after the initial components were formed. This research calculated the ICC scores by rotating these initial components, calculating the scores for four factors (accounting for 68% of the variance), and then creating a composite score. In conclusion, the principal components can be used to approximate installation capacity, without having to go through the entire process of creating the ICC scores. The results of this research effort can help answer the research questions posed in Chapter I.

Review of Research Questions

The questions posed in this research contribute to an effort focused on defining, understanding, and quantifying installation capacity. The results of this research and the answers to these questions can potentially aid Air Force analysts and planners in the event of major basing actions

1. What is installation capacity?

The Air Force has evaluated installation capacity in previous BRACs round and through several other instances such as Installation Development Plans and Base-to-Command briefings. However, the Air Force has not formally defined installation capacity in these instances. The Air Force must create an operational

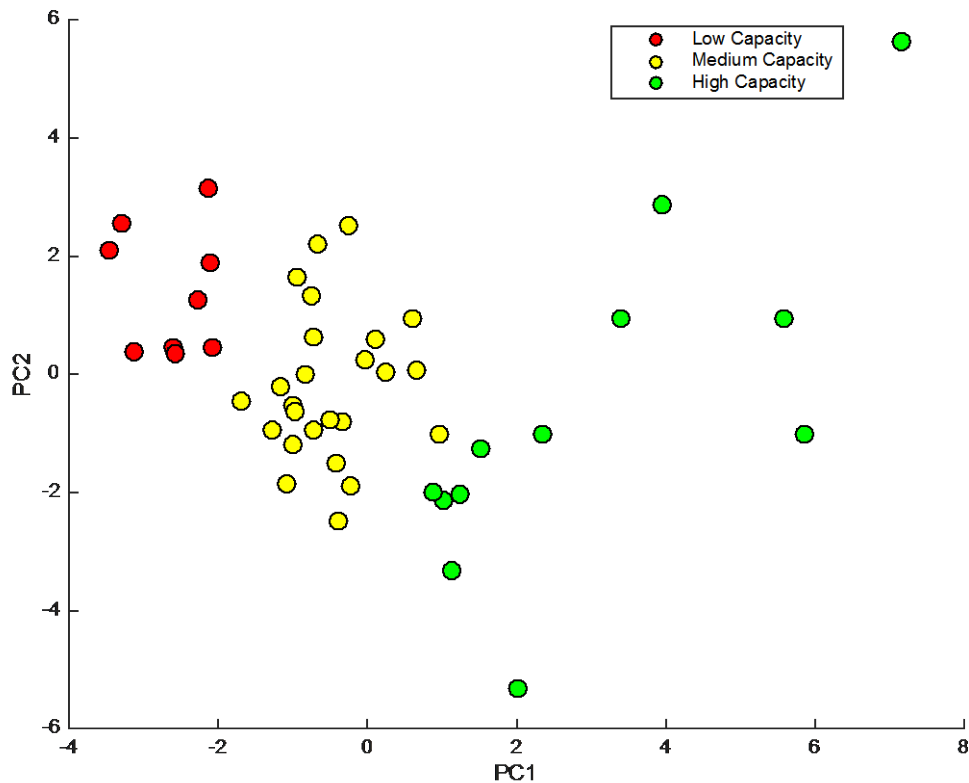


Figure 30: ICC PCA Classification Score Plot

definition of installation capacity before capacity can be measured. Through an in-depth literature review, this research proposed a definition of installation capacity in Chapter III, and remains the same following the analysis.

Installation capacity is the maximum quantity of mission assets and personnel that a base's built and natural infrastructure can support without significant degradation to the mission and quality of life.

2. What factors affect installation capacity?

The results of the factor analysis indicate that four factors appear to influence installation capacity: utility systems, airfield pavements and dormitories, natural infrastructure, and working facilities. Each factor contains at least two indicators of capacity. These four factors account for approximately 70% of the variance within the

capacity data, meaning that 30% of the data cannot be explained by the four factors found in the analysis.

3. What are the most significant factors to consider when determining installation capacity?

Based on the ICC results, utility systems and airfield pavement/dormitories prove to be the highest weighed factors, each contributing 28%. Working facilities and natural infrastructure contribute 24% and 20%, respectively. Although the weights differ, the factors generally contribute the same amount. Examining the individual variables, the administrative facility space and total base area variable have the highest estimated weights and water supply has the lowest weight. These weights were determined by comparing the individual ICC factor loadings to the entire ICC loadings matrix.

4. Can a metric be created to describe capacity at each installation and identify specific areas that do or do not exceed capacity?

This research developed a method to calculate a composite capacity score based on the results of the factor analysis. The weighted, individual factor scores combine to form the ICC, which is a measure of infrastructure capacity. The ICC reflects the current state of capacity at each installation and can be used as a single measure to objectively compare bases or as a dependent variable in a regression to predict impacts associated with mission changes. The factor scores provide information about how well an installation performs in a specific area. However, the factor scores and ICC scores do not identify areas where capacity is or is not exceeded.

Research Limitations

This research attempts to produce an objective and complete analysis of installation capacity. However several limitations exist in the study. These limitations must be identified and considered when interpreting the results and drawing conclusions about the research performed. The major limitations involve quality of data and method selection.

This research demonstrates a statistical method to analyze installation capacity, but the quality of the results depends completely on the quality of the data used. Quality of data refers to the accuracy, currency, and completeness of the data. The researcher made a significant effort to ensure the highest level of data quality. However, several issues are present that could affect the quality of the results: entry errors, inaccurate data, and outdated data.

The joint bases present one source of potentially inaccurate data. The researcher also used data from the 2005 BRAC, which contains outdated information. In addition to the outdated data, the researcher excluded several installations from the analysis because of a lack of available data. The results presented could change significantly with the complete set of CONUS installations because the methods used are sensitive to the addition of new observations. This methodology also includes inherent limitations.

The results produced from the multivariate techniques partially depend on the subjective judgment of the researcher performing the analysis. The researcher applied subjective judgment in the initial variable selection. The variable selection was based on the literature review, availability of data, and input from the committee members. These variables dictated the results of the PCA, EFA, and ICC scoring model. Consequently,

the results of this research would change, had a different set of variables been analyzed. In addition the variable selection, the dimensionality assessment, factor loadings interpretation, and composite score calculation included subjective judgment. For the dimensionality assessment, this research employed three heuristics to determine the number of components and factors to retain. However, the rules often suggested a different number of components, which forced the researcher to decide the appropriate number of components to retain for further analysis. Following this, the researcher interpreted the patterns in the loadings matrix. This interpretation can be performed using heuristics, but ultimately the researcher must apply their judgment and knowledge of the subject matter to interpret the loadings matrix. Finally, the method of calculating the ICC through factor scores was selected because this research primary focused on multivariate analysis. However, several other methods exist that can be used to create composite scores and the merits of the ICC model were not completely evaluated. However, the results of this research still provide valuable insight to the installations analyzed.

Recommendations for Future Work

Several opportunities exist for future research in this area. The first area involves improving on or building upon this research. As more data becomes available, the dataset can be updated and analyzed. Receiving new data or adding installations to the analysis could potentially change the results and further research may suggest altering the variables used in this analysis. Additionally, new methods could be used to evaluate capacity.

The study of urban carrying capacity is a relatively new area of research and several methods of evaluation exist. While this research focused on using PCA and EFA, the scientific community has not agreed on which method(s) are best for evaluating carrying capacity. Several articles were published during this research effort suggesting alternative methods to evaluate capacity. Future research could explore and apply these methods to evaluate installation capacity. Finally, future research work could be performed on evaluating community capacity.

This research focused primarily on the ability of an installation's infrastructure to support mission assets and personnel. The research evaluated indicators owned and controlled by the Air Force, but factors that affect installation capacity exist outside the fence. The ability of the surrounding communities to support an installation should also be considered when evaluating capacity. Adjacent communities provide significant support that is critical to the operation of an installation. Some examples of support provided by the community include: educational facilities and opportunities, healthcare facilities, off-base employment opportunities, and childcare.

Conclusion

The Air Force faces challenges today that have never been encountered before, and this trend will not change. To overcome the current challenges, as well as those not yet known, the air force must continue to adapt and find new solutions to these problems. This task includes maintaining a basing structure that meets strategic defense needs in the most efficient and effective manner possible. The Air Force may be required to make strategic basing decisions that close installations and relocate missions to achieve an optimal basing structure. However, before making these decisions, the Air Force needs

to have a comprehensive understanding about installation capacity. This research offers an in-depth analysis of capacity for the benefit of Air Force planners responsible for making or informing strategic basing decisions.

This research provides an operational definition of installation capacity, which is necessary for measuring installation-level, infrastructure capacity. Using this definition, the research evaluates a set of capacity indicators using multivariate techniques. The results of this analysis provide several benefits and insights. First, the EFA loadings matrices identify the underlying structure of the capacity data and determine what factors influence capacity. In addition, component and factor score plots provide a visual means for planners to better understand capacity characteristics of each installation and how they compare to others. Planners can also use the scores to determine the levels of capacity available at an installation. Finally, these scores are combined to create a composite score, the ICC, which measures the overall capacity at each installation. Going forward, the Air Force can use the results and insight gained from this research to develop an optimized basing structure that meets present, and future, defense needs.

Appendix A. Supply Variable Results

Table A - 1: Supply Variable Outliers

Variable	Base	Value
Permitted Air Pollutants (tpy)	Edwards	103,424
	Eglin	8,093
	Wright-Patterson	4,161
	Hanscom	2,160
	Tinker	1,667
	Robins	1,318
Water Quantity (gpd)	FE Warren	30,700,000
Wastewater Discharge Capacity (gpd)	Wright-Patterson	109,652,000
	Kirtland	100,000,000
	Minot	98,000,000
	Tinker	80,000,000
	Offutt	70,000,000
	Hill	34,000,000
Electrical Power Supply (MW)	Hill	1,468
Total Base Area (AC)	Eglin	453,594
	Edwards	308,300
	Holloman	52,055
	Kirtland	44,066
	McGuire	40,061
	Tyndall	29,276
	Beale	23,192
	Moody	21,859
	Barksdale	21,945
Maintenance Hangar (SF)	McGuire	786,870
	Andrews	1,045,323

Note: Highlighted installations excluded from analysis

Table A - 2: Supply Variable Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	2.89	29	29
2	1.62	16	45
3	1.45	15	60
4	1.22	12	72
5	0.92	9	81
6	0.63	6	87
7	0.56	6	93
8	0.46	5	98
9	0.16	2	99
10	0.09	1	100

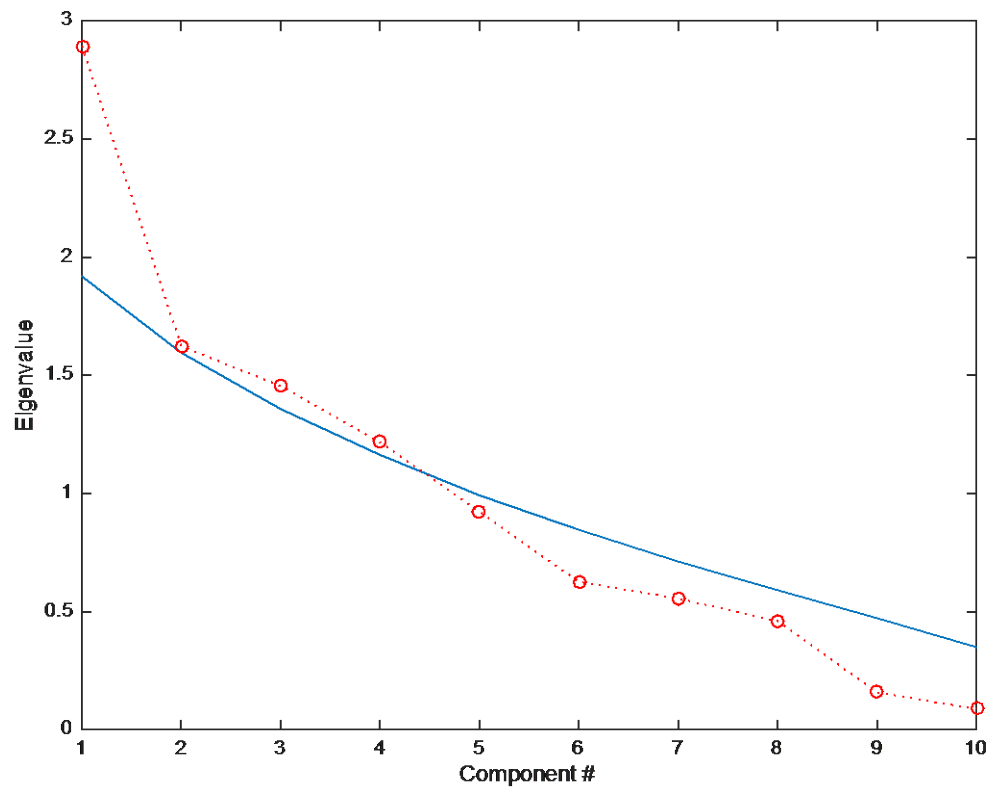


Figure A - 1: Supply Variable Scree Plot

Table A - 3: Supply Variable PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Permitted Air Pollutants	<u>-0.694</u>	-0.427	<u>-0.521</u>	-0.042
Water Quantity	0.015	<u>-0.522</u>	0.262	0.005
WW Discharge Capacity	-0.409	-0.457	<u>0.588</u>	0.061
Electrical Power Supply	<u>-0.735</u>	-0.253	0.246	0.162
Admin Facility Inventory	<u>-0.518</u>	-0.072	0.120	<u>0.673</u>
Total Base Area	<u>-0.634</u>	-0.142	<u>-0.674</u>	-0.174
Total Dorm Rooms	-0.408	0.450	0.392	-0.185
Runway Dimensions	-0.457	-0.099	0.285	<u>-0.688</u>
Apron Dimensions	<u>-0.662</u>	<u>0.580</u>	0.057	-0.216
MX Hangar Area	-0.469	<u>0.568</u>	-0.040	0.384
Eigenvalue	2.894	1.624	1.454	1.217

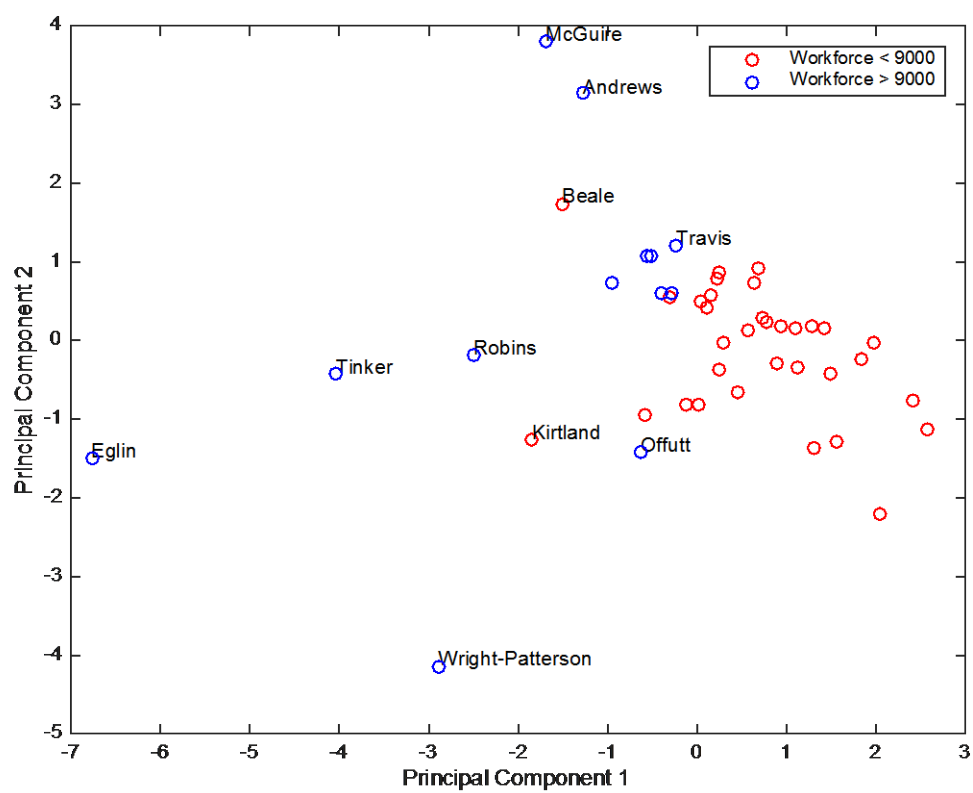


Figure A - 2: Supply Variable PCA Score Plot 1

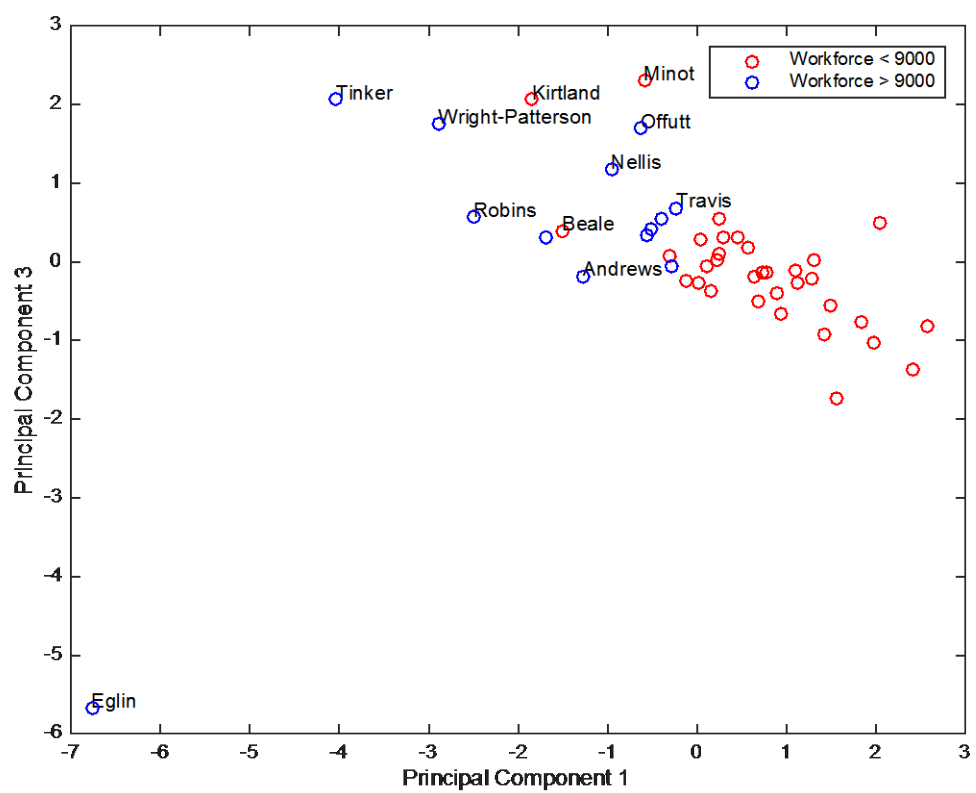


Figure A - 3: Supply Variable PCA Score Plot 2

Table A - 4: Supply Variable EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>-0.694</u>	-0.427	<u>-0.521</u>	-0.042	0.937
Water Quantity	0.015	<u>-0.522</u>	0.262	0.005	0.341
WW Discharge	-0.409	-0.457	<u>0.588</u>	0.061	0.726
Electrical Power Supply	<u>-0.735</u>	-0.253	0.246	0.162	0.690
Admin Facility Space	<u>-0.518</u>	-0.072	0.120	<u>0.673</u>	0.741
Total Base Area	<u>-0.634</u>	-0.142	<u>-0.674</u>	-0.174	0.907
Total Dorm Rooms	-0.408	0.450	0.392	-0.185	0.557
Runway Dimensions	-0.457	-0.099	0.285	<u>-0.688</u>	0.774
Apron Dimensions	<u>-0.662</u>	<u>0.580</u>	0.057	-0.216	0.824
MX Hangar Area	-0.469	<u>0.568</u>	-0.040	0.384	0.692
Eigenvalue	2.894	1.624	1.454	1.217	7.189

Table A - 5: Supply Indicator EFA Rotated Loadings

Kaiser's IFS = 0.61	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	-0.196	-0.026	<u>-0.939</u>	0.130	0.937
Water Quantity	<u>-0.524</u>	-0.238	0.021	-0.102	0.341
WW Discharge	<u>-0.829</u>	0.142	0.006	0.136	0.726
Electrical Power Supply	<u>-0.578</u>	0.294	-0.349	0.385	0.690
Admin Facility Space	-0.297	0.028	-0.149	<u>0.793</u>	0.741
Total Base Area	0.119	0.113	<u>-0.937</u>	0.042	0.907
Total Dorm Rooms	-0.077	<u>0.726</u>	0.121	0.097	0.557
Runway Dimensions	-0.408	<u>0.584</u>	-0.248	-0.452	0.774
Apron Dimensions	0.142	<u>0.847</u>	-0.231	0.185	0.824
MX Hangar Area	0.263	0.450	-0.072	<u>0.644</u>	0.692
Eigenvalue	1.698	1.964	2.039	1.488	7.189

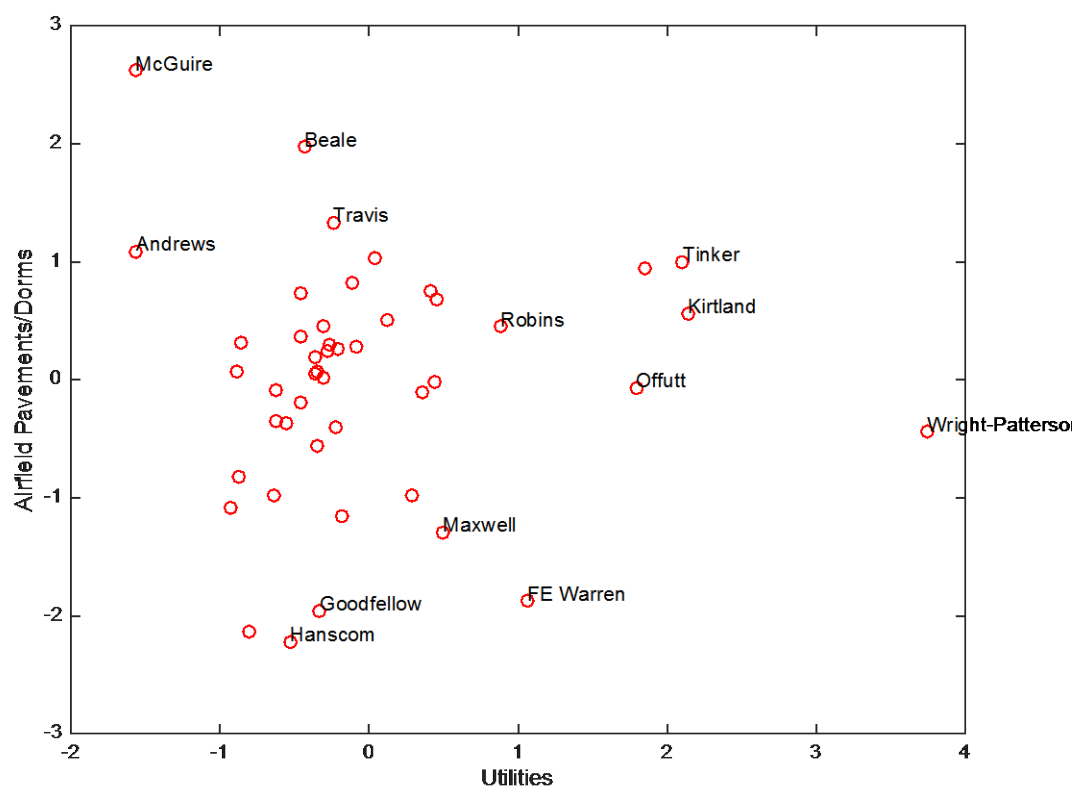


Figure A - 4: Supply Variable EFA Score Plot 1

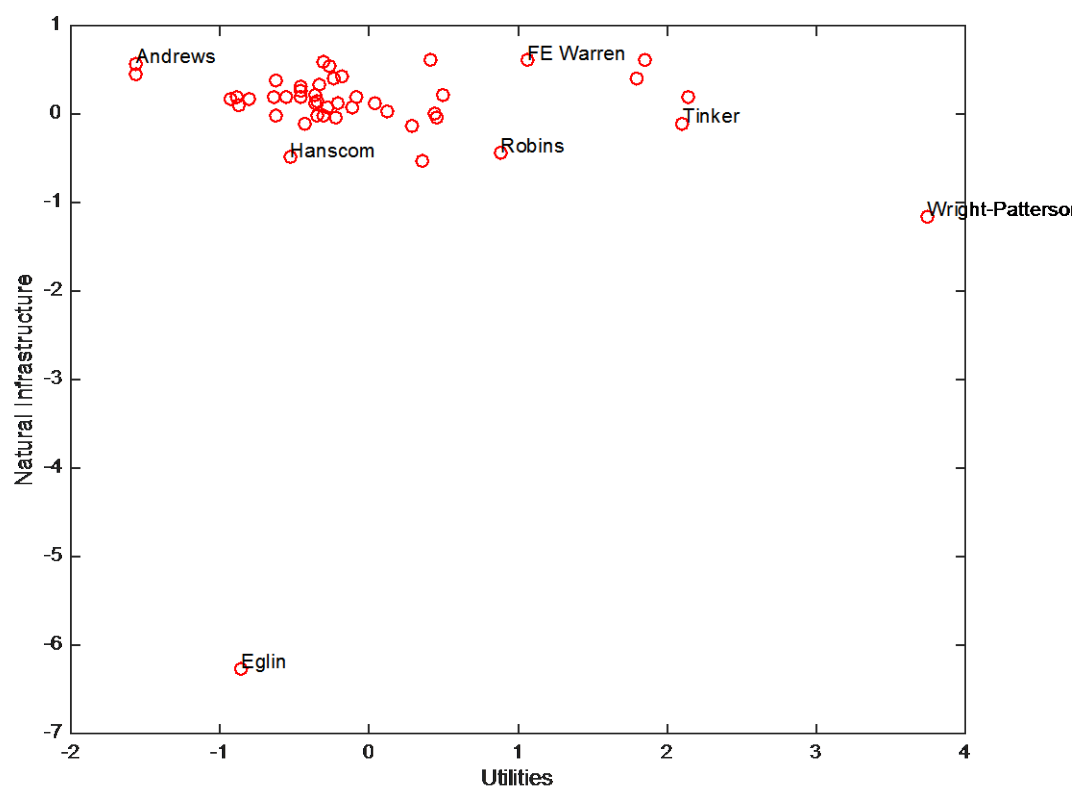


Figure A - 5: Supply Variable EFA Score Plot 2

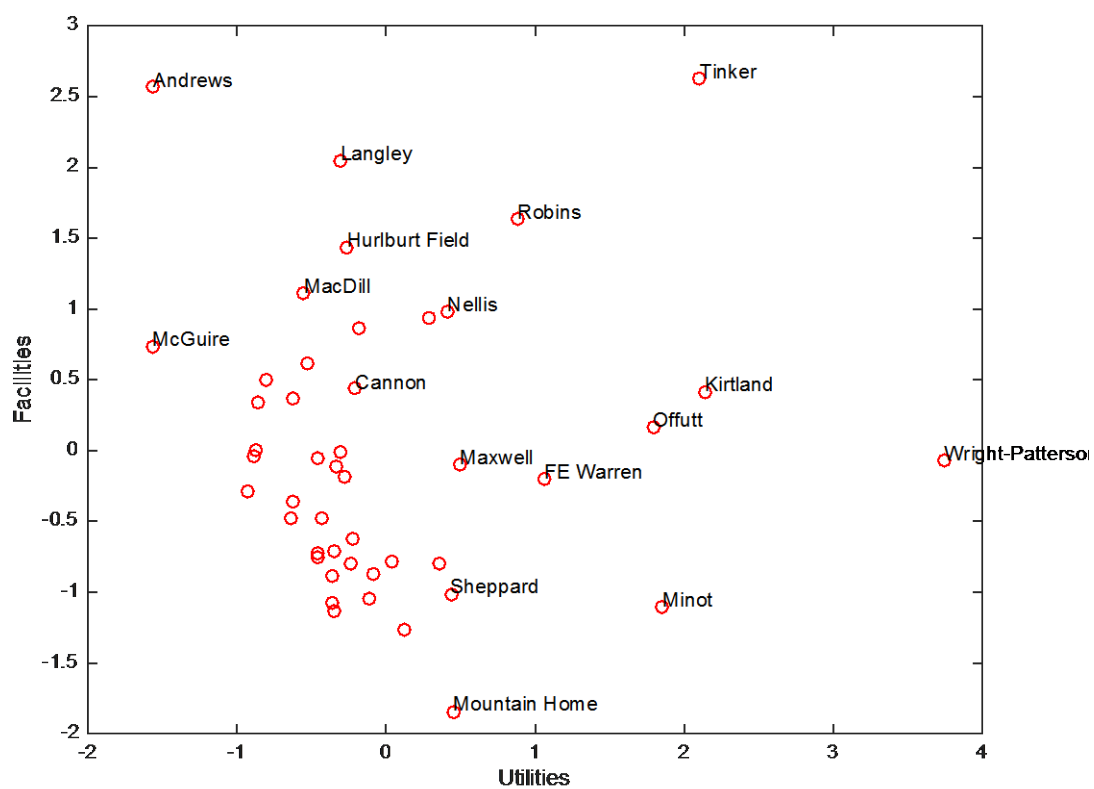


Figure A - 6: Supply Variable EFA Score Plot 3

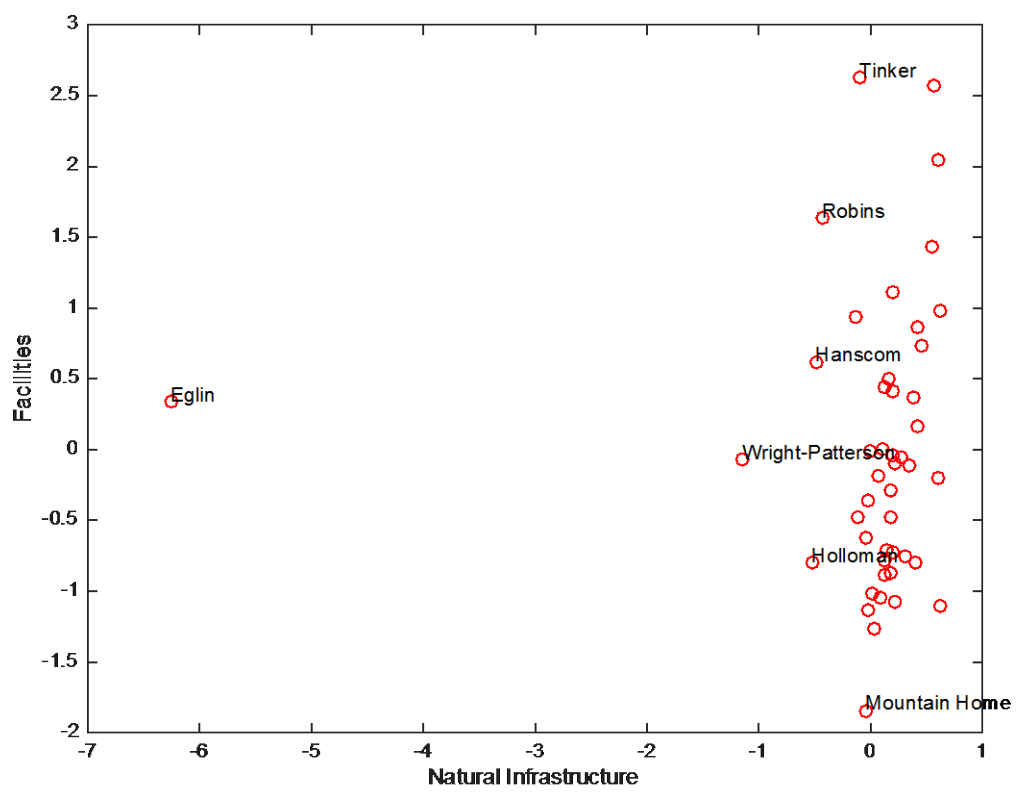


Figure A - 7: Supply Variable EFA Score Plot 4

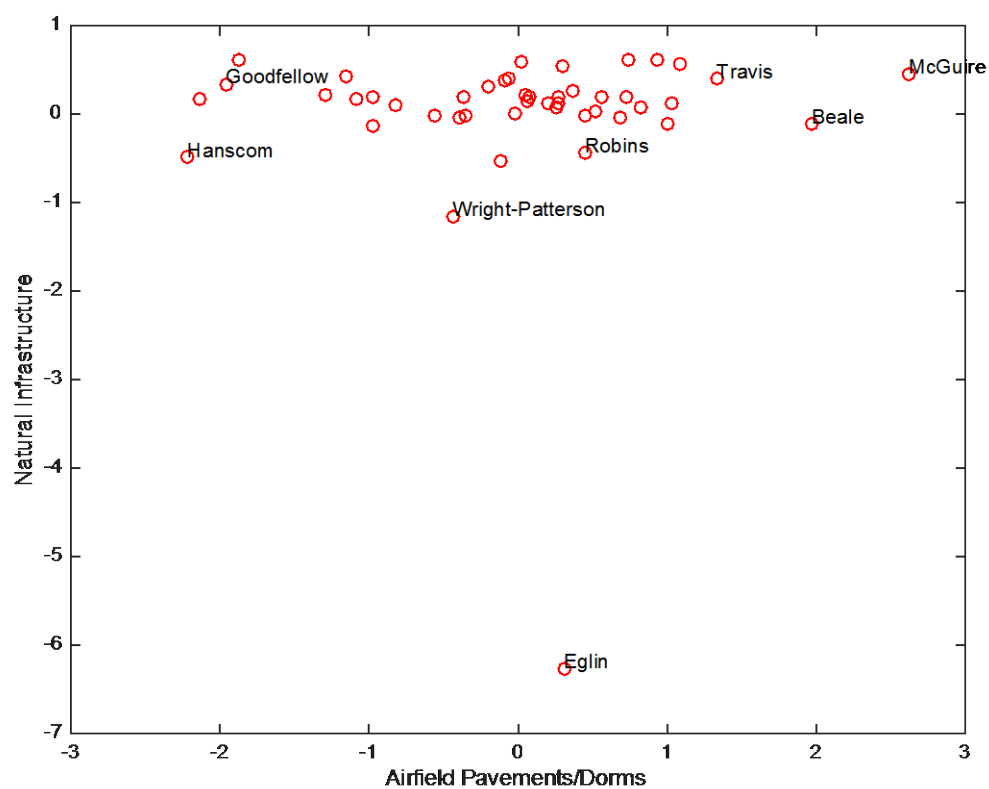


Figure A - 8: Supply Variable Score Plot 5

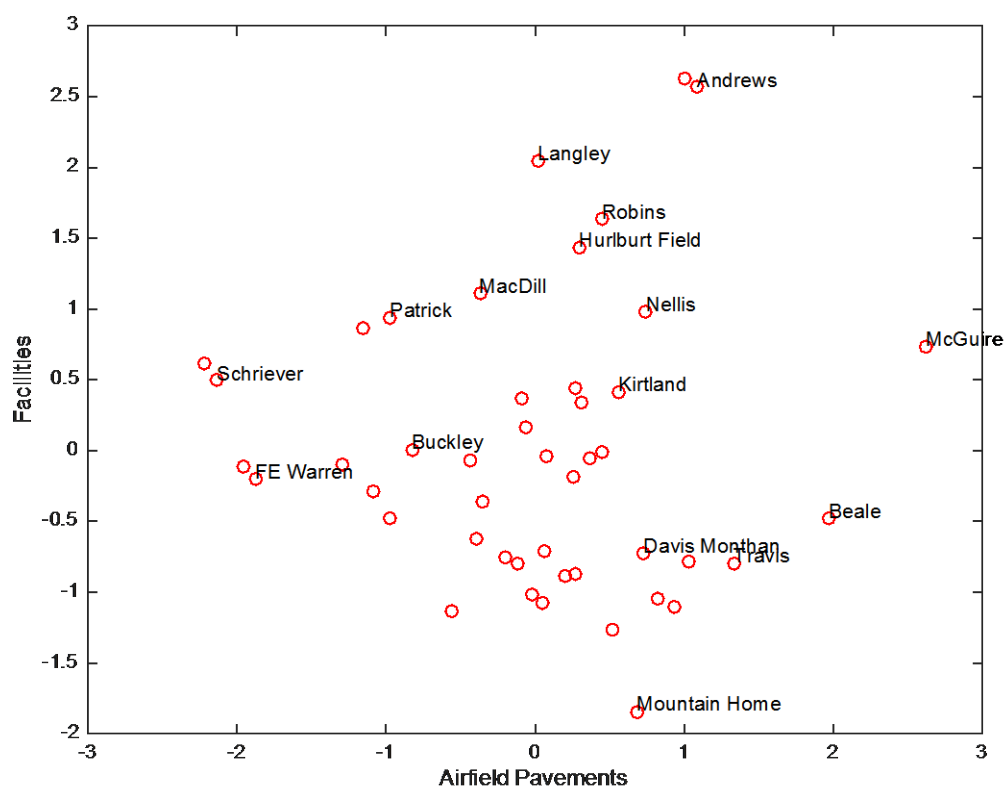


Figure A - 9: Supply Variable Score Plot 6

Appendix B. Demand Variable Results

Table B - 1: Demand Variable Outliers

Variable	Base	Value
Emitted Air Pollutants (tpy)	Wright-Patterson	1,102
	Peterson	422
	Tinker	406
	Hanscom	302
Wastewater Discharge Average Capacity (gpd)	Wright-Patterson	8,220,118
	Minot	7,900,000
	Barksdale	5,750,000
Electrical Power Average Demand (MW)	Wright-Patterson	82
	Robins	80
	Tinker	50
	Kirtland	41
	Edwards	40
Developed or Constrained Base Area (AC)	Edwards	305,203
	Eglin	72,255
	McGuire	39,150
	Holloman	34,404
	Kirtland	33,461
	Tyndall	28,348
	Moody	21,251
	Beale	19,155

Table B - 2: Demand Variable Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	2.97	30	30
2	2.24	22	52
3	1.31	13	65
4	1.07	11	76
5	0.71	7	83
6	0.48	5	88
7	0.42	4	92
8	0.34	3	95
9	0.29	3	98
10	0.17	2	100

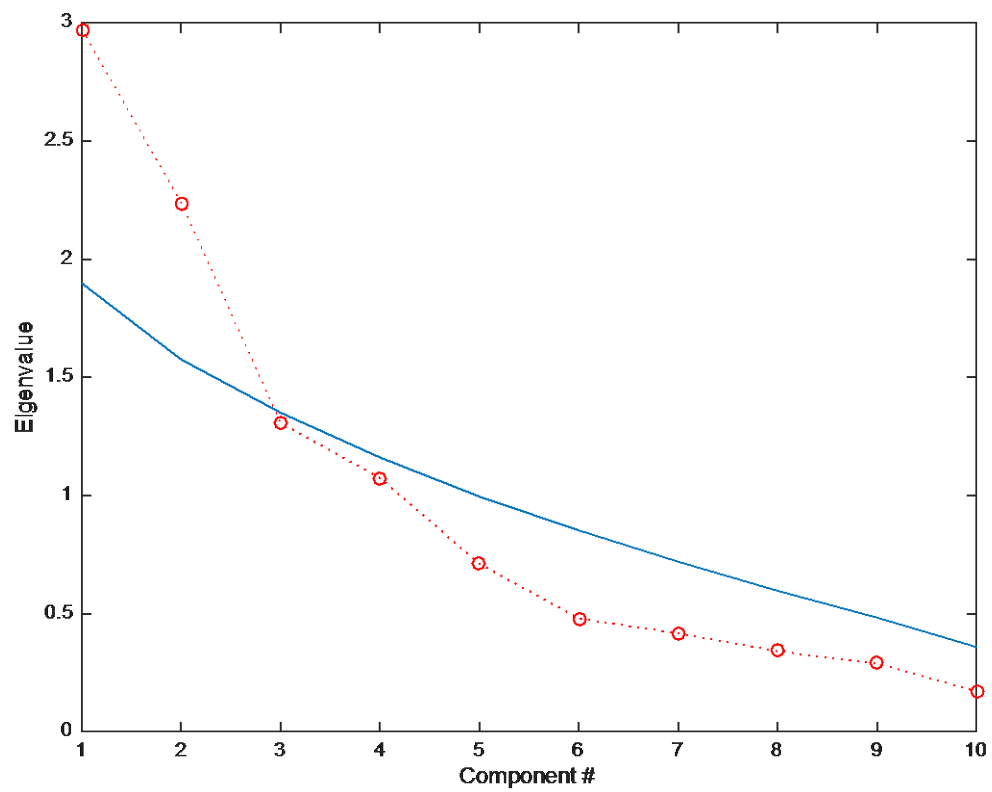


Figure B - 1: Demand Variable Scree Plot

Table B - 3: Demand Variable PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Emitted Air Pollutants	<u>-0.716</u>	-0.239	-0.336	0.034
Water Quantity Demand	<u>-0.791</u>	-0.002	0.130	-0.151
WW Discharge Demand	<u>-0.571</u>	0.246	<u>-0.669</u>	-0.107
Electrical Power Demand	<u>-0.910</u>	-0.132	0.020	0.036
Admin Facility Occupied	<u>-0.663</u>	-0.229	0.278	0.357
Developed/Constrained Area	-0.311	0.162	<u>0.556</u>	<u>-0.665</u>
Required Dorm Rooms	-0.122	<u>0.746</u>	-0.087	0.394
Required Runway Area	-0.135	<u>0.755</u>	-0.158	-0.417
Required Apron Area	0.121	<u>0.795</u>	-0.051	0.078
Required MX Hangar Area	-0.307	<u>0.515</u>	<u>0.554</u>	0.364
Eigenvalue	2.972	2.238	1.307	1.074

Table B - 4: Demand Variable EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Emitted Air Pollutants	<u>-0.716</u>	-0.239	-0.336	0.034	0.684
Water Quantity Demand	<u>-0.791</u>	-0.002	0.130	-0.151	0.666
WW Discharge Demand	<u>-0.571</u>	0.246	<u>-0.669</u>	-0.107	0.846
Electrical Power Demand	<u>-0.910</u>	-0.132	0.020	0.036	0.848
Admin Facility Occupied	<u>-0.663</u>	-0.229	0.278	0.357	0.697
Developed/Constrained Area	-0.311	0.162	<u>0.556</u>	<u>-0.665</u>	0.875
Required Dorm Rooms	-0.122	<u>0.746</u>	-0.087	0.394	0.735
Required Runway Area	-0.135	<u>0.755</u>	-0.158	-0.417	0.788
Required Apron Area	0.121	<u>0.795</u>	-0.051	0.078	0.655
Required MX Hangar Area	-0.307	<u>0.515</u>	<u>0.554</u>	0.364	0.799
Eigenvalue	2.972	2.238	1.307	1.074	7.592

Table B - 5: Demand Variable EFA Rotated Loadings

Kaiser's IFS = 0.58	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Emitted Air Pollutants	<u>-0.626</u>	-0.180	<u>-0.502</u>	0.088	0.684
Water Quantity Demand	<u>-0.691</u>	0.017	-0.241	-0.361	0.666
WW Discharge Demand	-0.270	0.181	<u>-0.859</u>	0.042	0.846
Electrical Power Demand	<u>-0.859</u>	-0.036	-0.292	-0.151	0.848
Admin Facility Occupied Developed/Constrained Area	<u>-0.819</u>	-0.009	0.144	0.066	0.697
	-0.162	-0.018	0.099	<u>-0.916</u>	0.875
Required Dorm Rooms	-0.051	<u>0.835</u>	-0.114	0.146	0.735
Required Runway Area	0.211	<u>0.550</u>	-0.456	-0.483	0.788
Required Apron Area	0.269	<u>0.751</u>	-0.107	-0.086	0.655
Required MX Hangar Area	-0.404	<u>0.677</u>	0.387	-0.167	0.799
Eigenvalue	2.661	2.089	1.546	1.296	7.592

Appendix C. Demand-Capacity Ratio Results

Table C - 1: Demand-Capacity Ratio Outliers

Variable	Base	Value
Air Pollutants	Peterson	0.697
Admin Facility Space	Vance	1.734

Note: Highlighted installations excluded from analysis

Table C - 2: Demand-Capacity Ratio Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	1.81	18%	18%
2	1.56	16%	34%
3	1.39	14%	48%
4	1.03	10%	58%
5	0.98	10%	68%
6	0.94	9%	77%
7	0.75	8%	85%
8	0.61	6%	91%
9	0.56	6%	96%
10	0.36	4%	100%

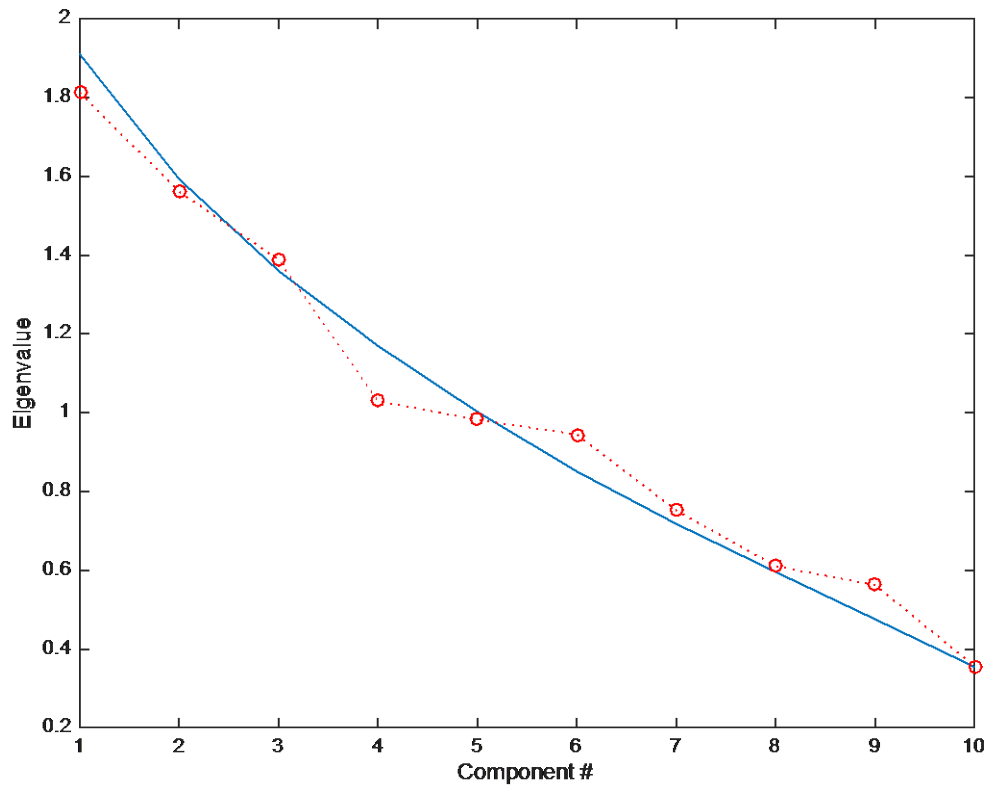


Figure C - 1: Demand-Capacity Ratio Scree Plot

Table C - 3: Demand-Capacity Ratio PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Air Pollutants	0.449	0.340	0.128	0.154
Water Quantity	0.110	<u>0.716</u>	-0.082	-0.474
WW Discharge	-0.152	0.407	0.245	<u>0.597</u>
Electrical Power	0.176	0.455	<u>-0.562</u>	0.013
Admin Facility Space	<u>0.546</u>	<u>-0.543</u>	-0.143	0.113
Base Area	-0.358	0.397	0.121	0.398
Dormitories	0.302	0.032	<u>0.714</u>	0.063
Runway	<u>-0.698</u>	0.076	0.040	-0.295
Apron	<u>-0.628</u>	-0.280	-0.370	0.287
MX Hangar Area	-0.381	-0.150	<u>0.554</u>	-0.282
Eigenvalue	1.813	1.561	1.388	1.029

Table C - 4: Demand-Capacity Ratio EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Air Pollutants	0.449	0.340	0.128	0.154	0.357
Water Quantity	0.110	<u>0.716</u>	-0.082	-0.474	0.756
WW Discharge	-0.152	0.407	0.245	<u>0.597</u>	0.605
Electrical Power	0.176	0.455	<u>-0.562</u>	0.013	0.555
Admin Facility Space	<u>0.546</u>	<u>-0.543</u>	-0.143	0.113	0.627
Base Area	-0.358	0.397	0.121	0.398	0.459
Dormitories	0.302	0.032	<u>0.714</u>	0.063	0.606
Runway	<u>-0.698</u>	0.076	0.040	-0.295	0.582
Apron	<u>-0.628</u>	-0.280	-0.370	0.287	0.692
MX Hangar Area	-0.381	-0.150	<u>0.554</u>	-0.282	0.553
Eigenvalue	1.813	1.561	1.388	1.029	5.791

Table C - 5: Demand-Capacity Ratio EFA Rotated Loadings

Kaiser's IFS = 0.57	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Air Pollutants	<u>0.539</u>	-0.012	-0.208	0.153	0.357
Water Quantity	0.315	<u>0.758</u>	-0.280	-0.066	0.756
WW Discharge	0.135	-0.033	-0.016	<u>0.765</u>	0.605
Electrical Power	0.030	0.238	<u>-0.705</u>	0.027	0.555
Admin Facility Space	0.166	<u>-0.641</u>	-0.128	-0.414	0.627
Base Area	-0.089	0.154	-0.005	<u>0.654</u>	0.459
Dormitories	<u>0.599</u>	-0.107	0.466	0.134	0.606
Runway	<u>-0.502</u>	0.480	0.307	0.077	0.582
Apron	<u>-0.786</u>	-0.166	-0.044	0.212	0.692
MX Hangar Area	-0.081	0.214	<u>0.708</u>	-0.009	0.553
Eigenvalue	1.678	1.382	1.449	1.282	5.791

Appendix D. Excess Variable Results

Table D - 1: Excess Variable Outliers

Variable	Base	Value
Air Pollutants (tpy)	Edwards	103,326
	Eglin	7,846
	Wright-Patterson	3,059
	Hanscom	1,858
	Robins	1,229
Water Quantity (gpd)	FE Warren	29,995,800
Wastewater Discharge Capacity (gpd)	Wright-Patterson	101,431,882
	Kirtland	98,548,232
	Minot	90,100,000
	Tinker	78,924,000
	Offutt	69,554,061
	Hill	33,298,268
Electrical Power (MW)	Hill	1,433
Admin Facility Space (SF)	Langley	699,375
	Tinker	552,953
Base Area (AC)	Eglin	381,339
	Kirtland	10,605
	Holloman	17,651
	Barksdale	5,470
Maintenance Hangar (SF)	McGuire	666,792
	Andrews	853,240

Note: Highlighted installations excluded from analysis

Table D - 2: Excess Variable Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	2.58	26	26
2	1.63	16	42
3	1.40	14	56
4	1.19	12	68
5	0.98	10	78
6	0.81	8	86
7	0.66	7	92
8	0.43	4	97
9	0.26	3	99
10	0.07	1	100

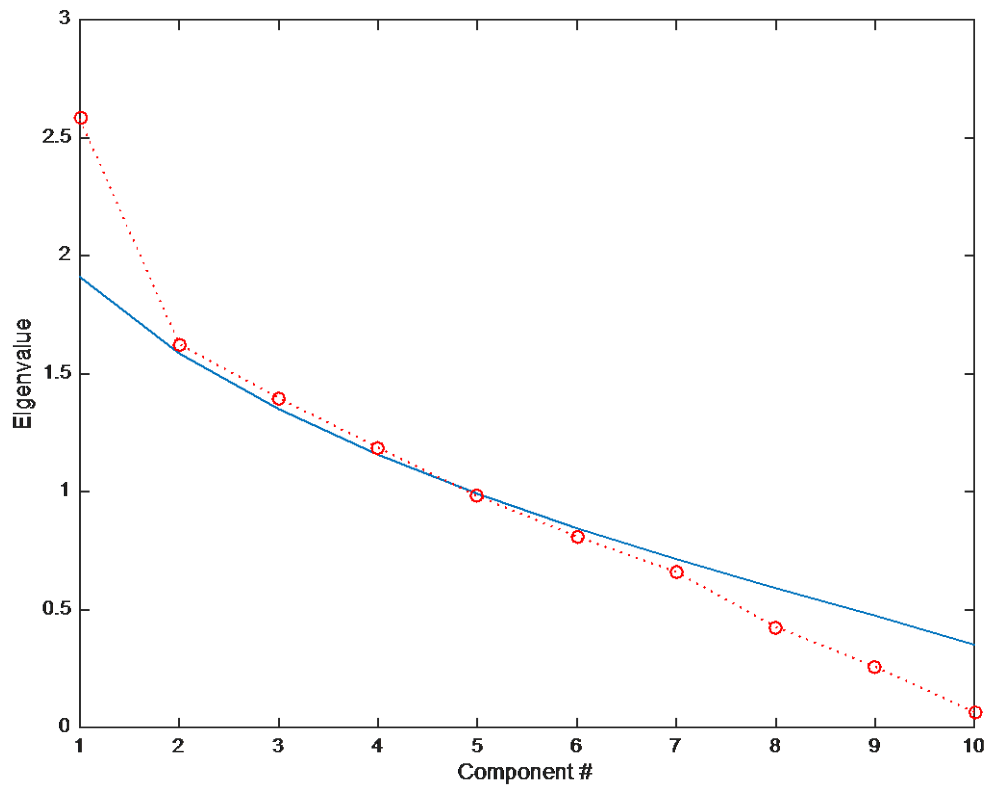


Figure D - 1: Excess Variable Scree Plot

Table D - 3: Excess Variable PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Air Pollutants	<u>0.813</u>	0.325	-0.037	0.399
Water Quantity	-0.139	0.409	-0.360	0.184
WW Discharge Capacity	0.147	0.130	<u>-0.805</u>	-0.221
Electrical Power	<u>0.633</u>	-0.134	-0.218	<u>-0.560</u>
Admin Facility Space	0.208	<u>-0.568</u>	-0.432	0.105
Base Area	<u>0.801</u>	0.249	0.177	0.443
Dormitories	-0.412	-0.068	<u>-0.536</u>	0.426
Runway	0.274	<u>0.618</u>	-0.218	-0.176
Apron	<u>0.677</u>	-0.329	0.082	-0.263
MX Hangar	0.299	<u>-0.661</u>	-0.107	0.379
Eigenvalue	2.581	1.626	1.398	1.187

Table D - 4: Excess Variable EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>0.813</u>	0.325	-0.037	0.399	0.927
Water Quantity	-0.139	0.409	-0.360	0.184	0.350
WW Discharge Capacity	0.147	0.130	<u>-0.805</u>	-0.221	0.736
Electrical Power Supply	<u>0.633</u>	-0.134	-0.218	<u>-0.560</u>	0.780
Admin Facility Inventory	0.208	<u>-0.568</u>	-0.432	0.105	0.564
Total Base Area	<u>0.801</u>	0.249	0.177	0.443	0.931
Total Dorm Rooms	-0.412	-0.068	<u>-0.536</u>	0.426	0.643
Runway Dimensions	0.274	<u>0.618</u>	-0.218	-0.176	0.536
Apron Dimensions	<u>0.677</u>	-0.329	0.082	-0.263	0.642
MX Hangar Area	0.299	<u>-0.661</u>	-0.107	0.379	0.682
Eigenvalue	2.581	1.626	1.398	1.187	6.791

Table D - 5: Excess Variable EFA Rotated Loadings

Kaiser's IFS = 0.69	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>0.942</u>	-0.038	-0.155	-0.118	0.927
Water Quantity	0.113	0.172	-0.364	0.419	0.350
WW Discharge	-0.035	-0.125	<u>-0.848</u>	-0.003	0.736
Electrical Power Supply	0.102	-0.101	-0.428	<u>-0.759</u>	0.780
Admin Facility Space	-0.034	<u>-0.708</u>	-0.226	-0.104	0.564
Total Base Area	<u>0.949</u>	-0.040	0.073	-0.155	0.931
Total Dorm Rooms	-0.151	-0.330	-0.264	<u>0.665</u>	0.643
Runway Dimensions	0.316	0.454	-0.476	-0.061	0.536
Apron Dimensions	0.252	-0.274	-0.025	<u>-0.709</u>	0.642
MX Hangar Area	0.178	<u>-0.787</u>	0.156	-0.077	0.682
Eigenvalue	2.031	1.570	1.436	1.754	6.791

Appendix E. ICC Results

Table E - 1: ICC Outliers

Variable	Base	Value
Permitted Air Pollutants (tpy)	Edwards	103,424
	Eglin	8,093
	Wright-Patterson	4,161
	Hanscom	2,160
	Tinker	1,667
	Robins	1,318
Emitted Air Pollutants (tpy)	Wright-Patterson	1,102
	Peterson	422
	Tinker	406
	Hanscom	302
Water Quantity (gpd)	FE Warren	30,700,000
Wastewater Discharge Capacity (gpd)	Wright-Patterson	109,652,000
	Kirtland	100,000,000
	Minot	98,000,000
	Tinker	80,000,000
	Offutt	70,000,000
	Hill	34,000,000
Wastewater Discharge Average Capacity (gpd)	Wright-Patterson	8,220,118
	Minot	7,900,000
	Barksdale	5,750,000
Electrical Power Supply (MW)	Hill	1,468
Electrical Power Average Demand (MW)	Wright-Patterson	82
	Robins	80
	Tinker	50
	Kirtland	41
	Edwards	40
Total Base Area (AC)	Eglin	453,594
	Edwards	308,300
	Holloman	52,055
	Kirtland	44,066
	McGuire	40,061
	Tyndall	29,276
	Beale	23,192
	Moody	21,859
	Barksdale	21,945
Developed or Constrained Base Area (AC)	Edwards	305,203
	Eglin	72,255
	McGuire	39,150
	Holloman	34,404
	Kirtland	33,461
	Tyndall	28,348
	Moody	21,251
	Beale	19,155
Maintenance Hangar (SF)	McGuire	786,870
	Andrews	1,045,323

Note: Highlighted installations excluded from analysis

Table E - 2: ICC Eigenvalues

Component	Eigenvalue	Variance (%)	Cumulative (%)
1	5.36	27	27
2	3.64	18	45
3	2.48	12	57
4	2.07	10	68
5	1.20	6	74
6	1.08	5	79
7	0.83	4	83
8	0.67	3	87
9	0.61	3	90
10	0.44	2	92
11	0.38	2	94
12	0.32	2	95
13	0.28	1	97
14	0.24	1	98
15	0.15	1	99
16	0.13	1	99
17	0.08	0	100
18	0.03	0	100
19	0.01	0	100
20	0.01	0	100

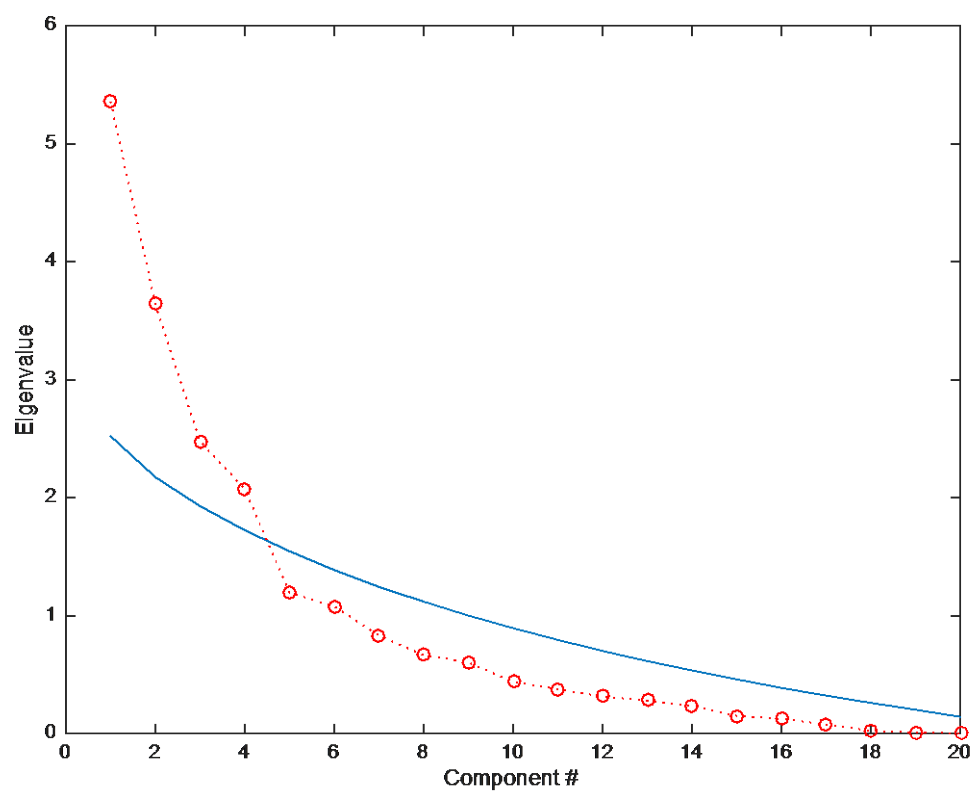


Figure E - 1: ICC Scree Plot

Table E - 3: ICC PCA Loadings

	PC 1	PC 2	PC 3	PC 4
Permitted Air Pollutants	<u>0.601</u>	0.223	0.404	<u>0.574</u>
Emitted Air Pollutants	<u>-0.563</u>	<u>-0.514</u>	0.182	-0.191
Water Quantity Supply	0.136	0.336	-0.279	0.076
Water Quantity Demand	<u>-0.637</u>	-0.291	0.278	0.130
WW Discharge Capacity	<u>0.583</u>	0.282	-0.493	0.019
WW Discharge Demand	<u>-0.524</u>	-0.102	<u>0.604</u>	-0.145
Electrical Power Supply	<u>0.734</u>	0.194	0.070	-0.055
Electrical Power Demand	<u>-0.801</u>	-0.427	0.090	0.070
Admin Facility Inventory	<u>0.588</u>	0.345	0.313	<u>-0.513</u>
Admin Facility Occupied	<u>-0.599</u>	-0.355	-0.315	0.489
Total Base Area	0.424	-0.134	<u>0.580</u>	<u>0.629</u>
Developed/Constrained Area	-0.461	0.310	-0.434	<u>-0.554</u>
Total Dorm Rooms	0.432	<u>-0.651</u>	-0.200	-0.170
Occupied Dorm Rooms	-0.450	<u>0.684</u>	0.150	0.130
Runway Dimensions	0.482	-0.178	-0.422	0.346
Required Runway Area	-0.263	<u>0.595</u>	0.461	-0.130
Apron Dimensions	<u>0.529</u>	<u>-0.605</u>	0.187	-0.099
Required Apron Area	-0.079	<u>0.685</u>	0.280	-0.008
MX Hangar Area	0.402	-0.371	0.387	-0.361
Required MX Hangar Area	-0.476	0.457	-0.265	0.358
Eigenvalue	5.359	3.640	2.480	2.073

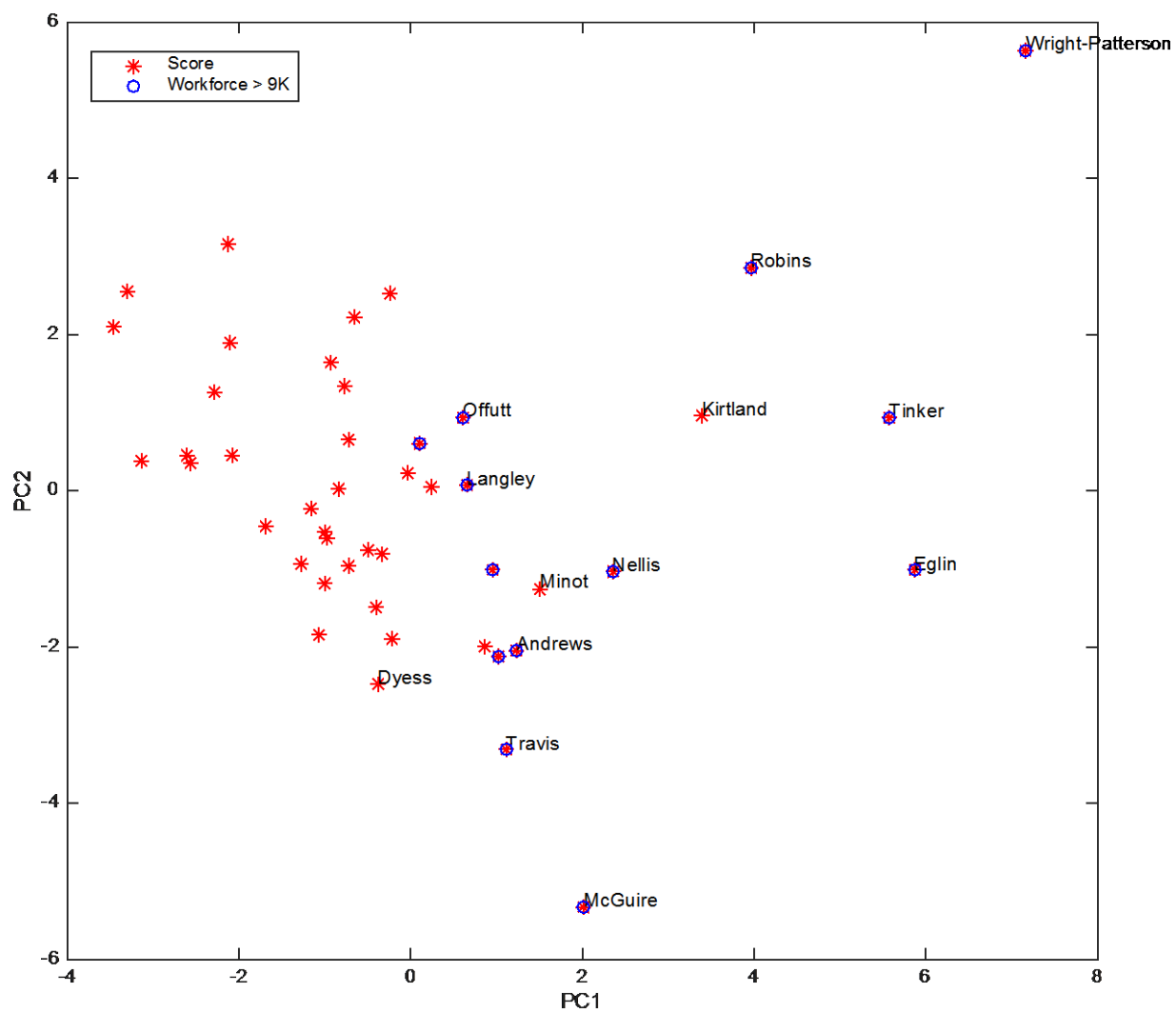


Figure E - 2: ICC PCA Score Plot 1

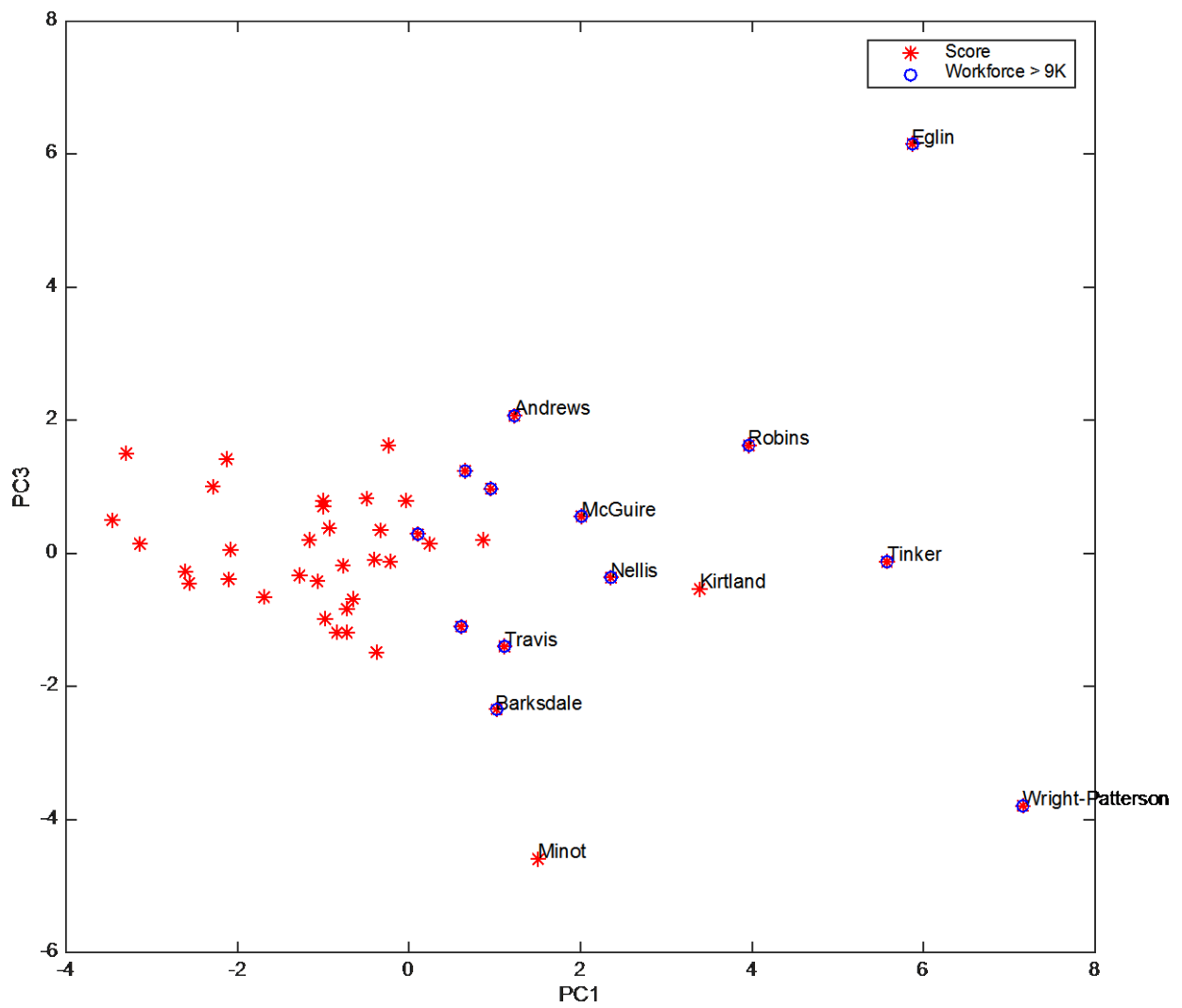


Figure E - 3: ICC PCA Score Plot 2

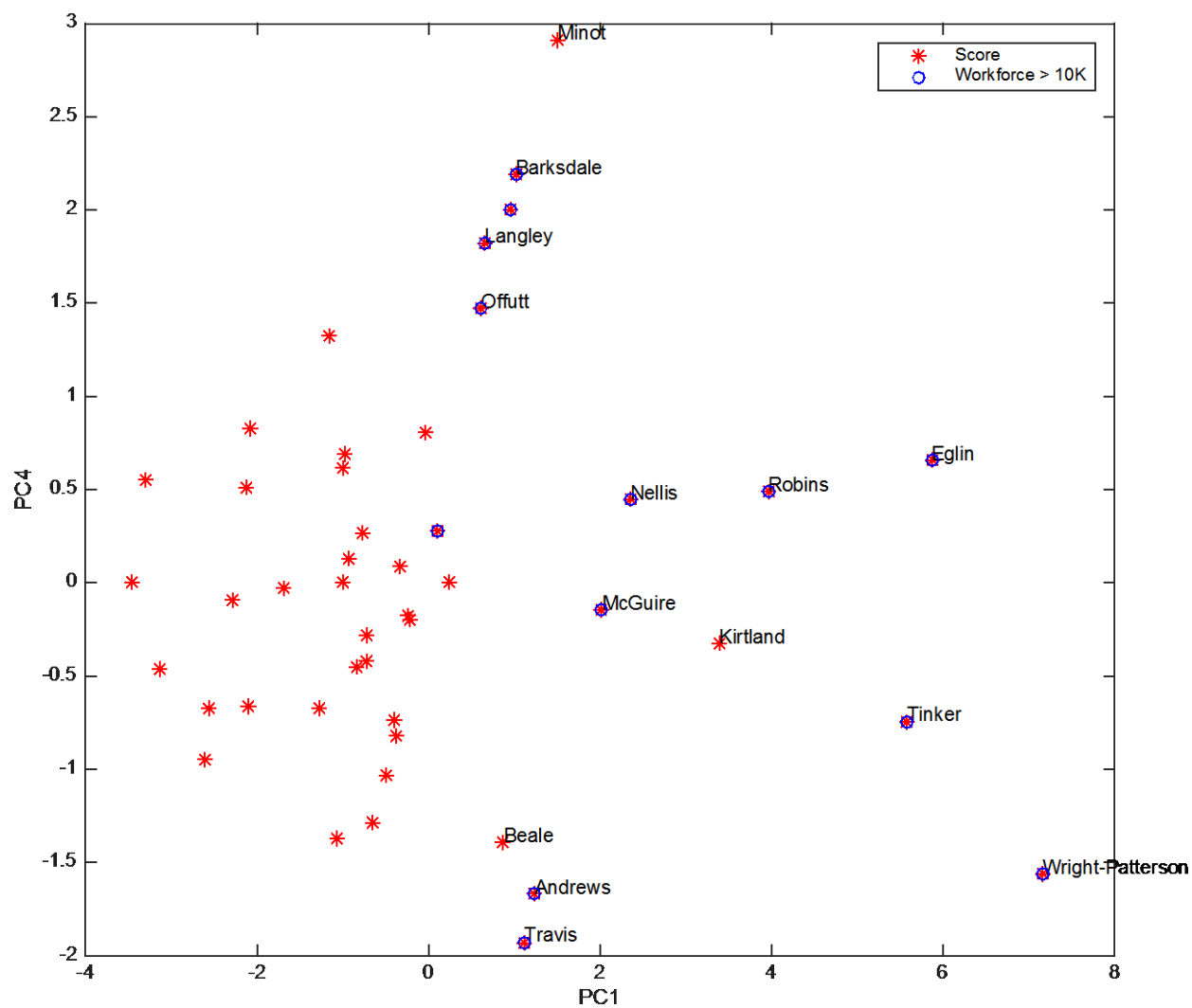


Figure E - 4: ICC PCA Score Plot 3

Table E - 4: ICC EFA Un-Rotated Loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	<u>0.601</u>	0.223	0.404	<u>0.574</u>	0.904
Emitted Air Pollutants	<u>-0.563</u>	<u>-0.514</u>	0.182	-0.191	0.651
Water Quantity Supply	0.136	0.336	-0.279	0.076	0.215
Water Quantity Demand	<u>-0.637</u>	-0.291	0.278	0.130	0.584
WW Discharge Capacity	<u>0.583</u>	0.282	-0.493	0.019	0.663
WW Discharge Demand	<u>-0.524</u>	-0.102	<u>0.604</u>	-0.145	0.671
Electrical Power Supply	<u>0.734</u>	0.194	0.070	-0.055	0.585
Electrical Power Demand	<u>-0.801</u>	-0.427	0.090	0.070	0.837
Admin Facility Inventory	<u>0.588</u>	0.345	0.313	<u>-0.513</u>	0.825
Admin Facility Occupied	<u>-0.599</u>	-0.355	-0.315	0.489	0.824
Total Base Area	0.424	-0.134	<u>0.580</u>	<u>0.629</u>	0.929
Developed/Constrained Area	-0.461	0.310	-0.434	<u>-0.554</u>	0.805
Total Dorm Rooms	0.432	<u>-0.651</u>	-0.200	-0.170	0.680
Occupied Dorm Rooms	-0.450	<u>0.684</u>	0.150	0.130	0.710
Runway Dimensions	0.482	-0.178	-0.422	0.346	0.561
Required Runway Area	-0.263	<u>0.595</u>	0.461	-0.130	0.652
Apron Dimensions	<u>0.529</u>	<u>-0.605</u>	0.187	-0.099	0.691
Required Apron Area	-0.079	<u>0.685</u>	0.280	-0.008	0.554
MX Hangar Area	0.402	-0.371	0.387	-0.361	0.579
Required MX Hangar Area	-0.476	0.457	-0.265	0.358	0.633
Eigenvalue	5.359	3.640	2.480	2.073	13.553

Table E - 5: ICC EFA Rotated Loadings

Kaiser's IFS = 0.64	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Permitted Air Pollutants	0.181	0.139	-0.317	<u>0.867</u>	0.904
Emitted Air Pollutants	-0.188	-0.211	<u>0.720</u>	-0.229	0.651
Water Quantity Supply	-0.048	0.180	-0.419	-0.071	0.215
Water Quantity Demand	-0.351	0.079	<u>0.674</u>	0.006	0.584
WW Discharge Capacity	0.118	-0.102	<u>-0.798</u>	-0.040	0.663
WW Discharge Demand	0.086	0.250	<u>0.775</u>	0.020	0.671
Electrical Power Supply	<u>0.503</u>	-0.104	-0.487	0.289	0.585
Electrical Power Demand	<u>-0.517</u>	-0.032	<u>0.727</u>	-0.199	0.837
Admin Facility Inventory	<u>0.874</u>	0.091	-0.229	0.022	0.825
Admin Facility Occupied	<u>-0.868</u>	-0.099	0.244	-0.044	0.824
Total Base Area	0.065	-0.053	0.050	<u>0.959</u>	0.929
Developed/Constrained Area	-0.031	0.269	-0.024	<u>-0.855</u>	0.805
Total Dorm Rooms	0.125	<u>-0.811</u>	-0.083	0.000	0.680
Occupied Dorm Rooms	-0.125	<u>0.829</u>	0.055	-0.067	0.710
Runway Dimensions	-0.208	-0.407	<u>-0.548</u>	0.229	0.561
Required Runway Area	0.281	<u>0.725</u>	0.218	0.004	0.652
Apron Dimensions	0.325	<u>-0.700</u>	0.068	0.301	0.691
Required Apron Area	0.230	<u>0.702</u>	-0.071	0.060	0.554
MX Hangar Area	<u>0.572</u>	-0.427	0.216	0.153	0.579
Required MX Hangar Area	<u>-0.534</u>	<u>0.562</u>	-0.131	-0.125	0.633
Eigenvalue	3.181	3.796	3.799	2.777	13.553

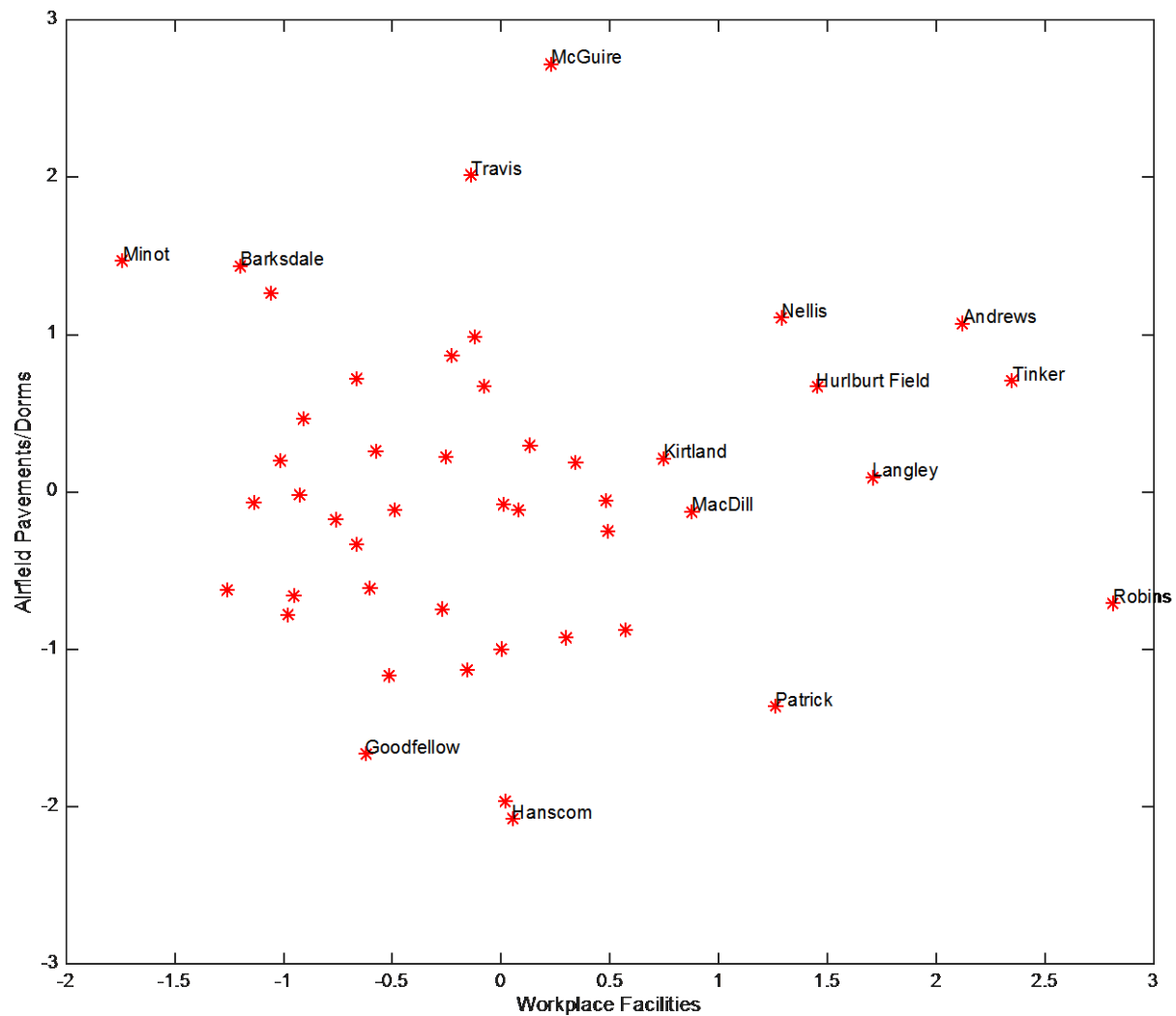


Figure E - 5: ICC EFA Score Plot 1

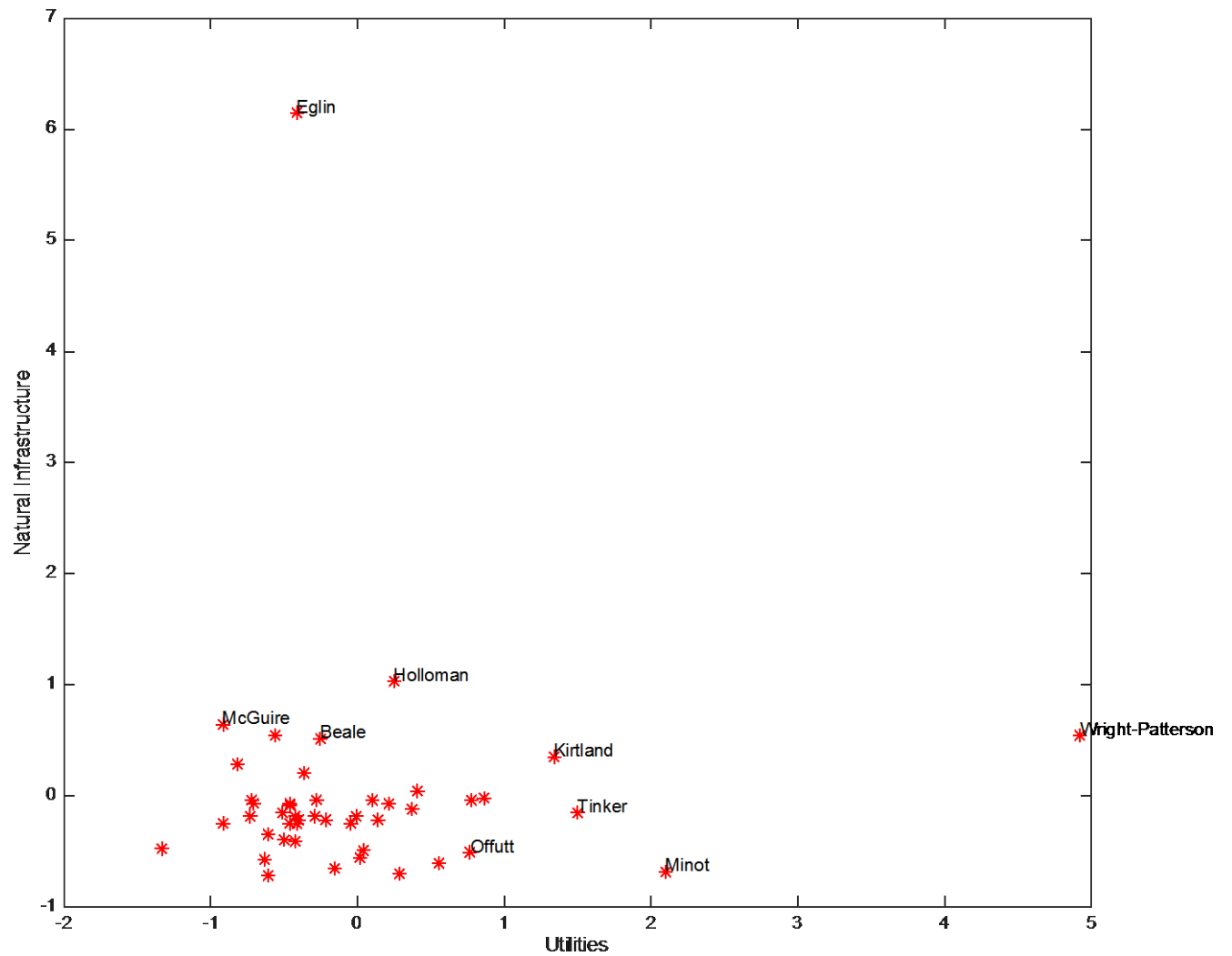


Figure E - 6: ICC EFA Score Plot 2

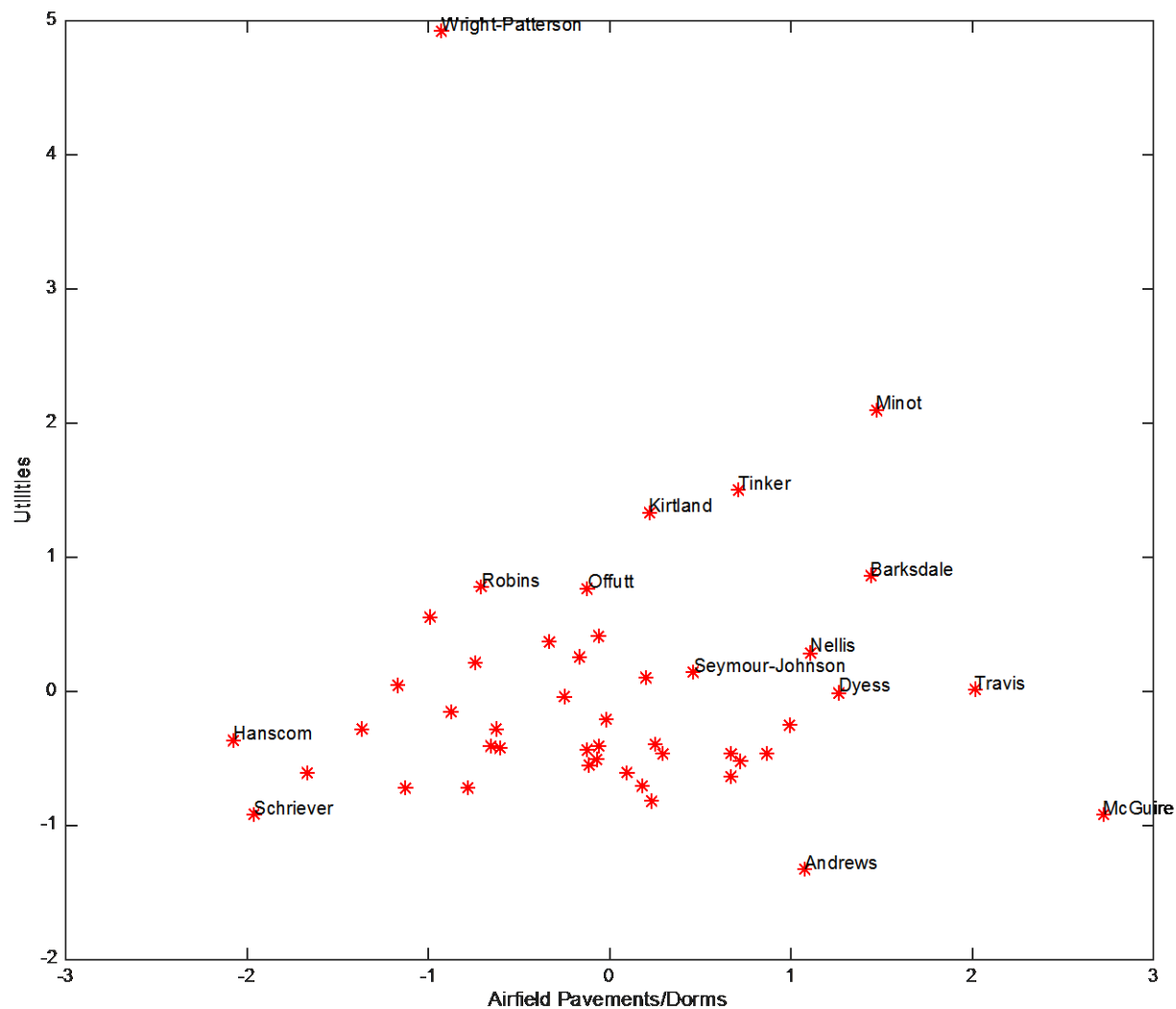


Figure E - 7: ICC EFA Score Plot 3

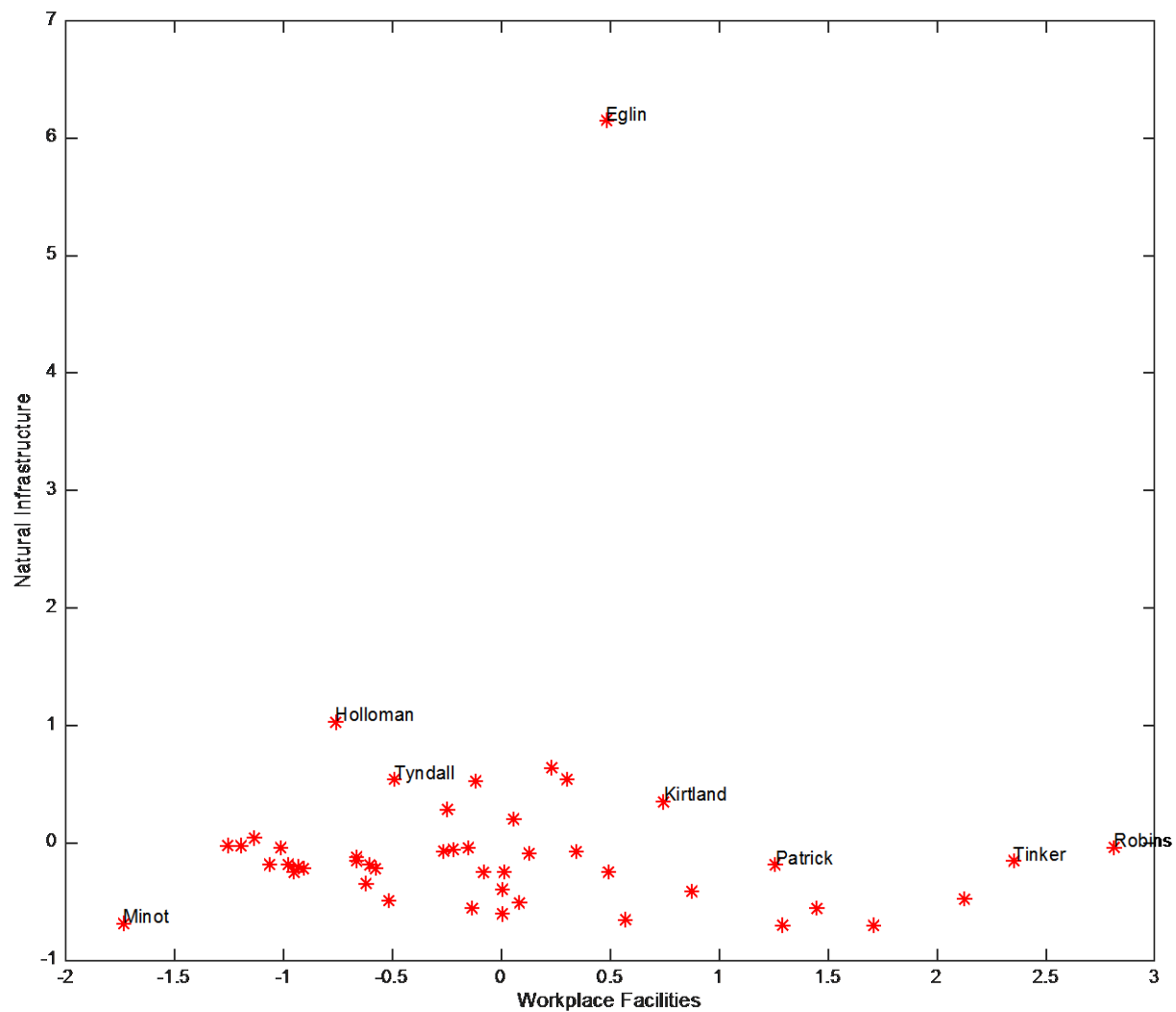


Figure E - 8: ICC EFA Score Plot 4

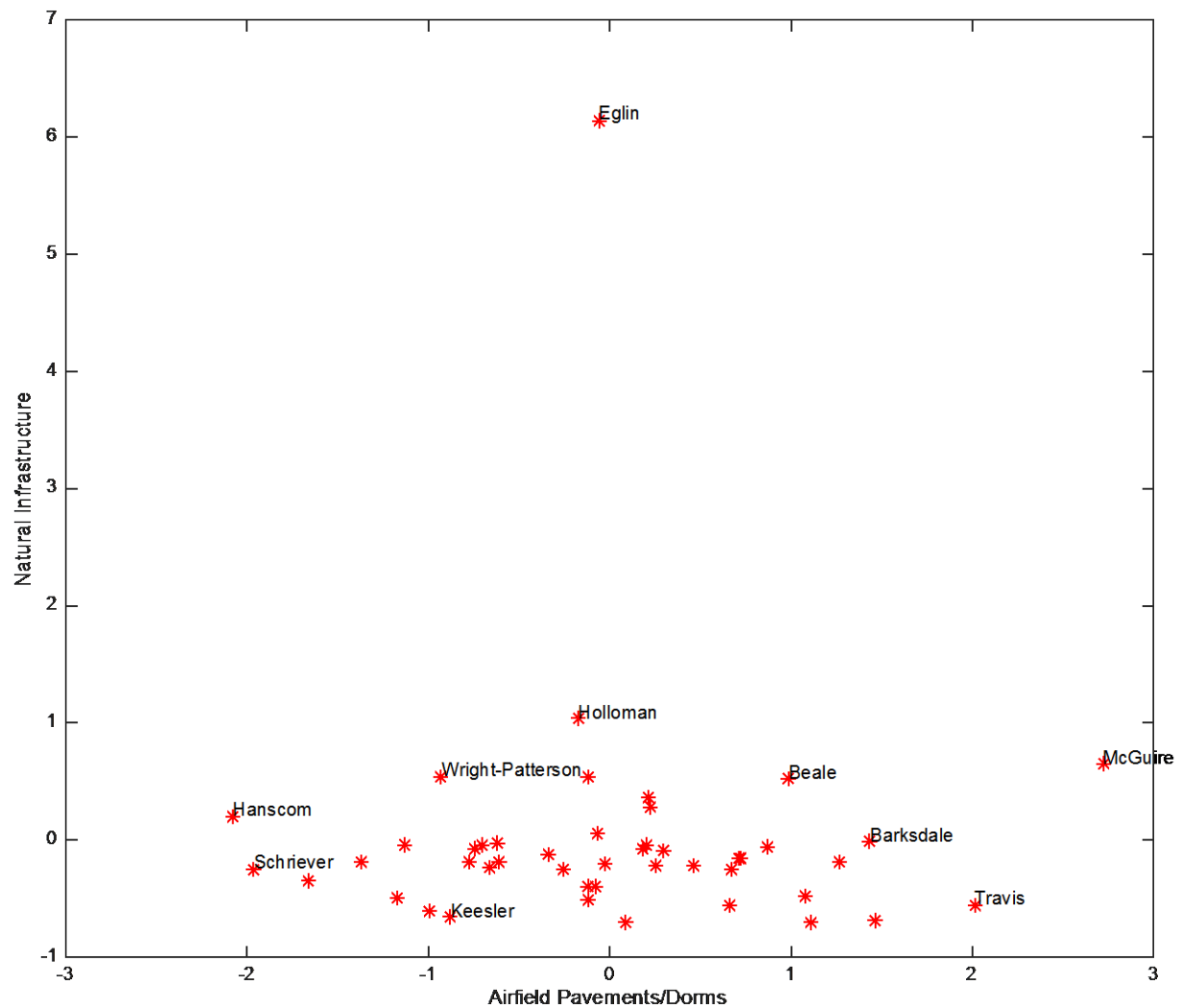


Figure E - 9: ICC EFA Score Plot 5

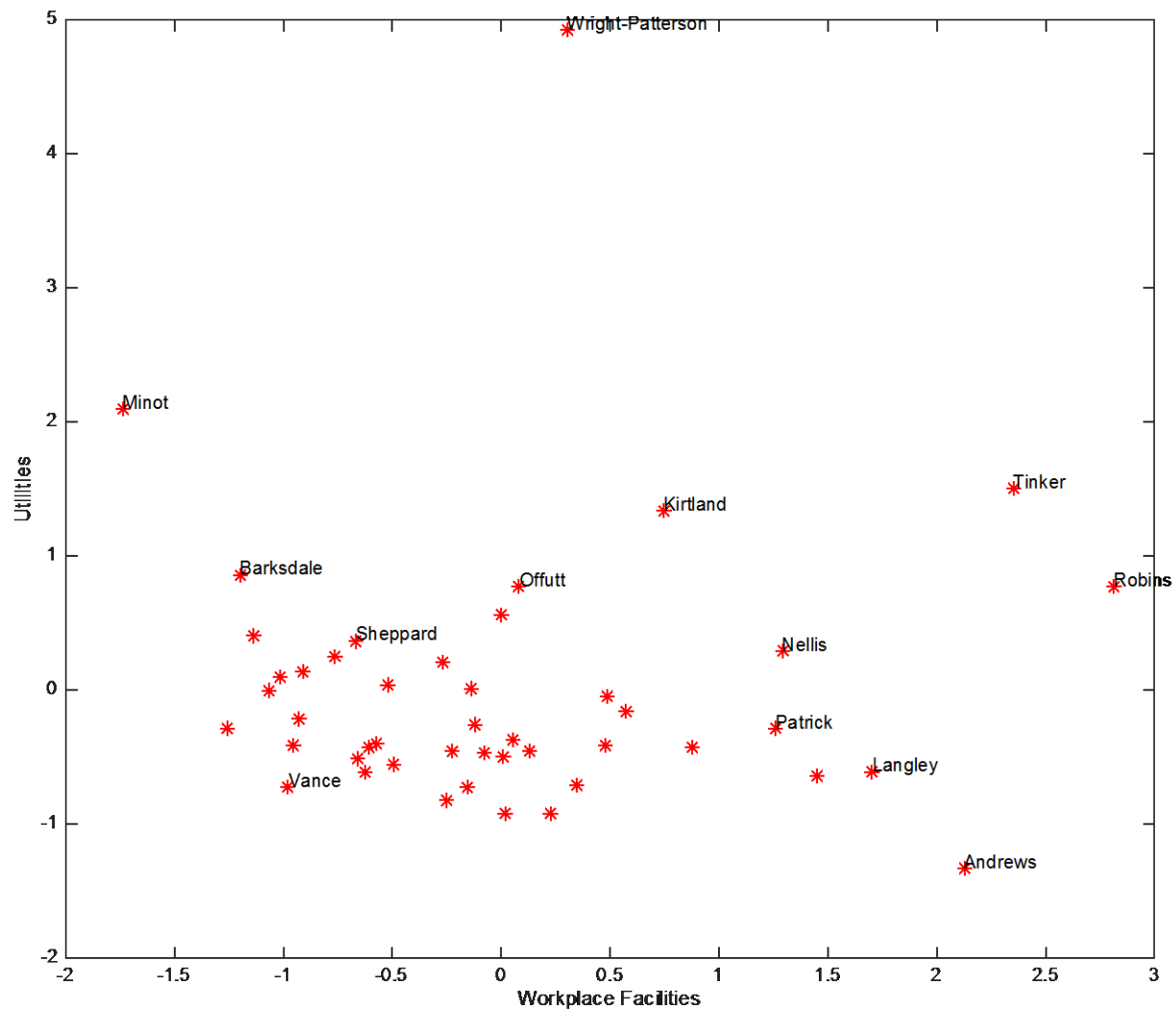


Figure E - 10: ICC EFA Score Plot 6

Table E - 6: ICC Factor Weights

Factor	Classification	Weight
1	"Workplace Facilities"	23.5%
2	"Airfield Pavements/Dorms"	28.0%
3	"Utility Systems"	28.0%
4	"Natural Infrastructure"	20.5%

Table E - 7: ICC Individual Variable Weights

<u>Variable</u>	<u>Weight</u>
Permitted Air Pollutants	6.93%
Emitted Air Pollutants	4.78%
Water Quantity Supply	1.62%
Water Quantity Demand	4.19%
WW Discharge Capacity	5.87%
WW Discharge Demand	5.54%
Electrical Power Supply	2.33%
Electrical Power Demand	4.88%
Admin Facility Inventory	7.04%
Admin Facility Occupied	6.94%
Total Base Area	8.47%
Developed/Constrained Area	6.73%
Total Dorm Rooms	6.06%
Occupied Dorm Rooms	6.33%
Runway Dimensions	2.77%
Required Runway Area	4.84%
Apron Dimensions	4.52%
Required Apron Area	4.54%
MX Hangar Area	3.01%
Required MX Hangar Area	2.63%

Table E - 8: Factor and ICC Scores

<u>Installation</u>	<u>Workplace Facilities</u>	<u>Airfield Pavements/Dorms</u>	<u>Utilities</u>	<u>Natural Infrastructure</u>	<u>ICC</u>
Wright-Patterson	0.303	-0.928	4.921	0.546	1.303
Eglin	0.479	-0.060	-0.413	6.144	1.239
Tinker	2.351	0.708	1.500	-0.154	1.139
McGuire	0.230	2.721	-0.919	0.645	0.690
Kirtland	0.747	0.216	1.336	0.356	0.683
Robins	2.813	-0.705	0.774	-0.036	0.672
Nellis	1.290	1.106	0.291	-0.694	0.552
Minot	-1.739	1.467	2.097	-0.682	0.451
Travis	-0.139	2.011	0.012	-0.550	0.421
Barksdale	-1.199	1.437	0.859	-0.015	0.359
Andrews	2.124	1.075	-1.330	-0.482	0.328
Beale	-0.121	0.989	-0.253	0.520	0.284
Hurlburt Field	1.451	0.666	-0.634	-0.564	0.234
Langley	1.704	0.094	-0.610	-0.709	0.110
Offutt	0.083	-0.120	0.769	-0.512	0.097
Dyess	-1.063	1.262	-0.007	-0.186	0.064
Holloman	-0.761	-0.170	0.249	1.033	0.055
Davis Monthan	-0.225	0.866	-0.460	-0.062	0.048
Little Rock	-0.080	0.669	-0.463	-0.250	-0.012
Scott	0.491	-0.251	-0.039	-0.247	-0.017
MacDill	0.877	-0.124	-0.431	-0.402	-0.032
Whiteman	0.129	0.294	-0.461	-0.091	-0.035
Cannon	0.347	0.182	-0.710	-0.075	-0.082
Seymour-Johnson	-0.911	0.463	0.139	-0.217	-0.090
Dover	-0.663	0.720	-0.516	-0.151	-0.130
Ellsworth	-1.011	0.201	0.103	-0.039	-0.160
Mountain Home	-1.136	-0.063	0.404	0.049	-0.161
Moody	-0.249	0.228	-0.821	0.290	-0.165
Sheppard	-0.667	-0.338	0.371	-0.116	-0.171
Tyndall	-0.492	-0.115	-0.554	0.542	-0.192
Patrick	1.260	-1.365	-0.288	-0.187	-0.205
Altus	-0.576	0.255	-0.400	-0.222	-0.221
Peterson	-0.267	-0.745	0.211	-0.071	-0.227

Shaw	0.008	-0.076	-0.503	-0.397	-0.242
Maxwell	0.001	-0.993	0.558	-0.604	-0.245
Keesler	0.571	-0.877	-0.155	-0.660	-0.290
Luke	-0.931	-0.023	-0.218	-0.207	-0.328
Malmstrom	-0.607	-0.605	-0.424	-0.179	-0.468
FE Warren	-0.519	-1.172	0.046	-0.497	-0.539
Columbus	-1.259	-0.625	-0.283	-0.028	-0.556
Buckley	-0.156	-1.132	-0.716	-0.041	-0.563
Laughlin	-0.956	-0.661	-0.411	-0.241	-0.574
Hanscom	0.053	-2.076	-0.365	0.203	-0.630
Vance	-0.977	-0.778	-0.727	-0.179	-0.687
Goodfellow	-0.625	-1.665	-0.605	-0.340	-0.852
Schriever	0.015	-1.961	-0.920	-0.242	-0.853

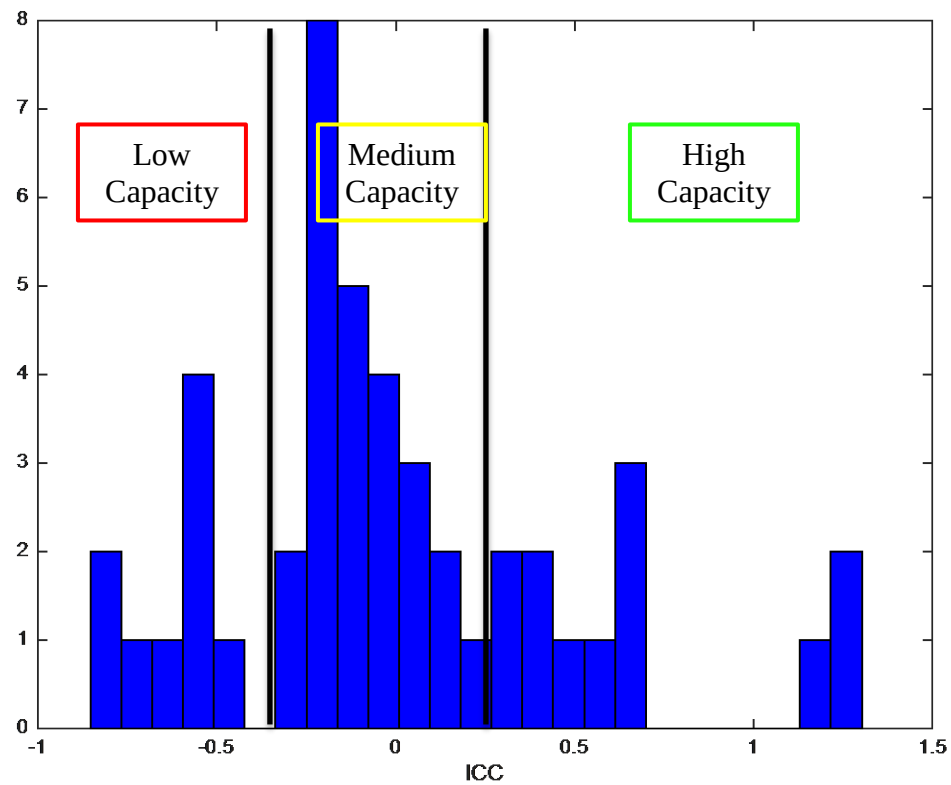


Figure E - 11: ICC Score Distribution

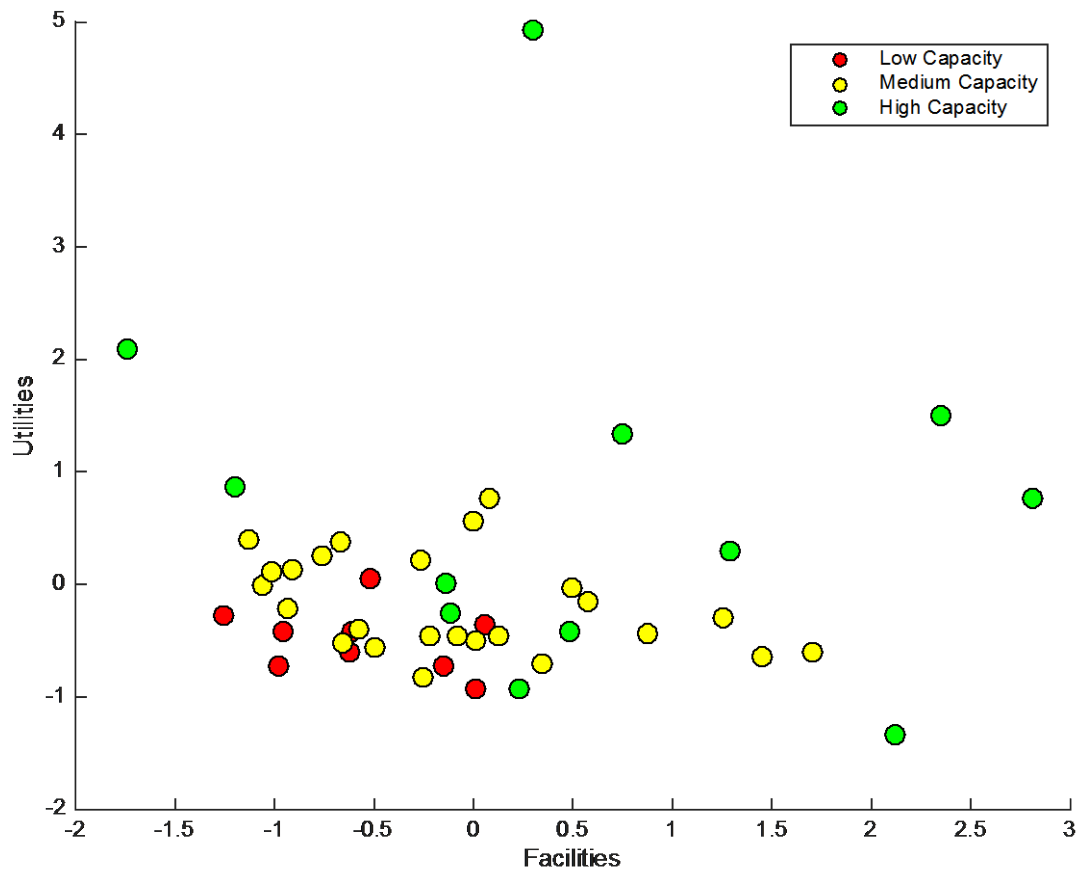


Figure E - 12: ICC EFA Classification Score Plot 1

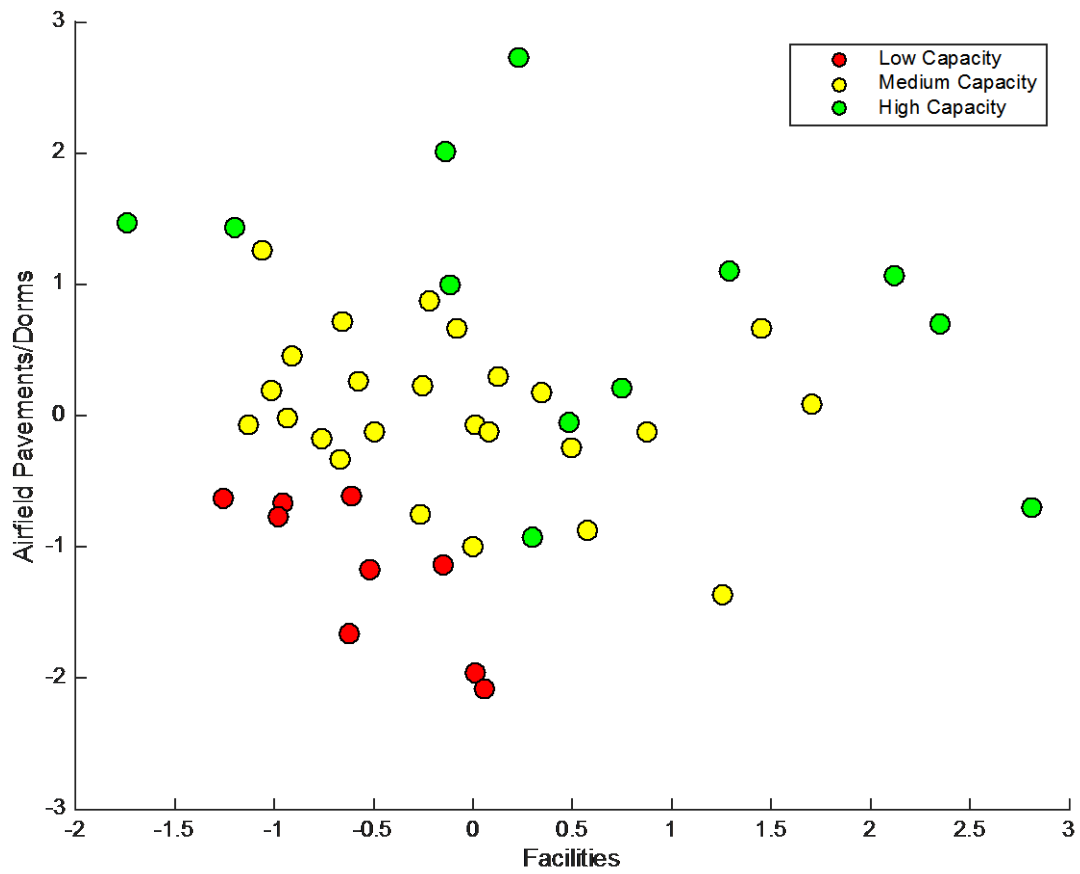


Figure E - 13: ICC EFA Classification Score Plot 2

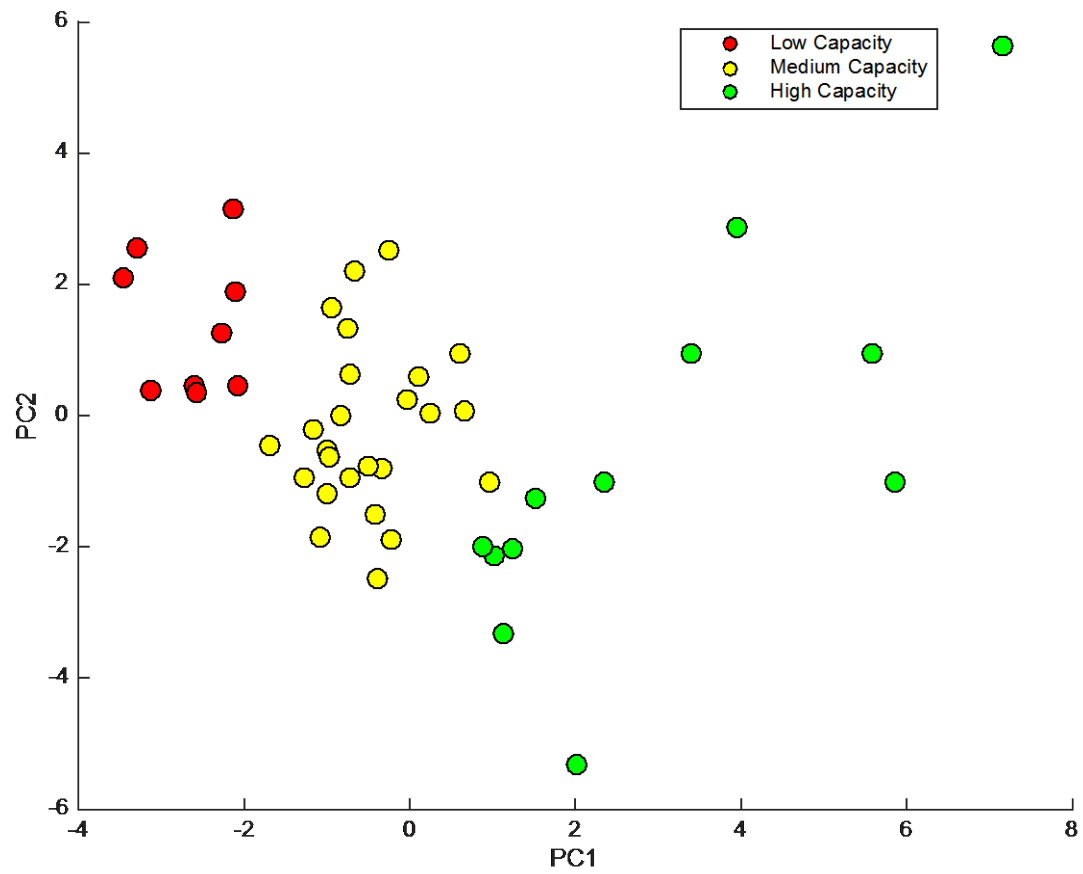


Figure E - 14: ICC PCA Classification Score Plot

Appendix F. Nearest Neighbor Regression MATLAB Script

Nearest Neighbor Regression

```
known = xlsread('Installation Capacity Data.xlsx','ICI_Working','N5:AG22');
work = xlsread('Installation Capacity Data.xlsx','ICI_Working','C5:C22');
space_invent = known(:,9);
space_req = known(:,10);
trng = [work space_invent space_req];

unk = xlsread('Installation Capacity Data.xlsx','ICI_Working','N23:AG52');
uwork = xlsread('Installation Capacity Data.xlsx','ICI_Working','C23:C52');
uspace_invent = unk(:,9);
learning = [uwork uspace_invent];

%Calculating distances of unknown points to known points
for x = 1:30 %30 unknown values
    point = learning(x,:);
    for n = 1:18 %18 know values
        distance(x,n) = sqrt((trng(n,1)-point(1,1))^2 + (trng(n,2)-
point(1,2))^2);
    end
end
dist = distance';
k=3;

%for each unknown value, calculating average of k nearest instances
for x = 1:30
    ntrng = [trng dist(:,x)];
    [Y,I]=sort(ntrng(:,4));
    sorted = ntrng(I,:);
    estimate = mean(sorted(1:k,3));
    learning(x,3) = estimate;
end
```

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Appendix G. Sample PCA/EFA MATLAB Script

Sample MATLAB Code: Supply Variable PCA

```
%Loading raw data
ICI = xlsread('Installation Capacity Data.xlsx','Supply_ICI','N5:AG50');
s = size(ICI);

%removing demand columns
sICI = ICI(:,1:2:s(1,2));

supply_corr = corr(sICI);
[eigenvectors, eigenvalues] = eig(supply_corr)

%Loadings matrix
loadings = eigenvectors*sqrt(eigenvalues)

%Horn's Curve, N=46,p=10
[curvepoints] = Hornscurve(46,10);
figure
plot(curvepoints);hold on
B = sort(diag(eigenvalues),'descend'); %Scree plot of eigenvalues
plot(B,':ro') xlabel('Component #') ylabel('Eigenvalue')

% Computing the scores with standardized data
scores = zscore(sICI)*eigenvectors;
```

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Sample MATLAB Code: Supply Variable EFA

```
%Loading raw data
ICI = xlsread('Installation Capacity Data.xlsx','Supply_ICI','N5:AG50');
s = size(ICI);

%Removing demand columns
sICI = ICI(:,1:2:s(1,2));

supply_corr = corr(sICI);
[eigenvectors, eigenvalues] = eig(supply_corr)

%Horn's Curve, N=46,p=10
[curvepoints] = Hornscurve(46,10);
figure
plot(curvepoints);hold on
B = sort(diag(eigenvalues),'descend'); %Scree plot of eigenvalues
plot(B,':ro') xlabel('Component #') ylabel('Eigenvalue')
```

```

%Calculate loadings
v1 = eigenvalues(1,1);e1 = eigenvectors(:,1);L1 = sqrt(v1)*e1;var1 = v1/10;
v2 = eigenvalues(2,2);e2 = eigenvectors(:,2);L2 = sqrt(v2)*e2;var2 = v2/10;
v3 = eigenvalues(3,3);e3 = eigenvectors(:,3);L3 = sqrt(v3)*e3;var3 = v3/10;
v4 = eigenvalues(6,6);e4 = eigenvectors(:,6);L4 = sqrt(v4)*e4;var4 = v4/10;
Total_Variance_Explained = (var1+var2+var3+var4)*100
L = [L1 L2 L3 L4];

%Un-rotated eigenvalues, and communalities %Communalities
for n = 1:10
    h(n) = L(n,1)^2+L(n,2)^2+L(n,3)^2+L(n,4)^2;
end
h_2 = h';

%Eigenvalues
eig_1=sum(L1(:).^2);
eig_2=sum(L2(:).^2);
eig_3=sum(L3(:).^2);
eig_4=sum(L4(:).^2);
Sum = eig_1+eig_2+eig_3+eig_4;

%Kaiser's IFS
Unrotated_IFS = IFS2(L)

%Varimax Rotation
%Rotated Loadings
B = rotatefactors(L);

%Communalities
for n = 1:10
    rh(n) = B(n,1)^2+B(n,2)^2+B(n,3)^2+B(n,4)^2;
end
rh_2 = rh';

%Eigenvalues
reig_1=sum(B(:,1).^2);
reig_2=sum(B(:,2).^2);
reig_3=sum(B(:,3).^2);
reig_4=sum(B(:,4).^2);
Sum = reig_1+reig_2+reig_3+reig_4;

%Kaiser's IFS
Rotated_IFS = IFS2(B)

%Computing the scores with the rotated loadings
scores = zscore(sICI)*inv(supply_corr)*B;

```

Appendix H. ICC MATLAB Script

ICC Normalization/EFA/Composite Scoring

```
ICI = xlsread('Installation Capacity Data.xlsx','Final_ICI','N5:AG50');
size_class = xlsread('Installation Capacity Data.xlsx','Final_ICI','D5:D50');
[num,txt,row] = xlsread('Installation Capacity
Data.xlsx','Final_ICI','A5:A50');
%Odd columns are supply (positive) indicators
%Even columns are demand (negative) indicators
s = size(ICI);

%%Normalization
for c = 1:s(1,2)
    %If odd_even = 0, then even, if odd_even = 1, then odd.
    odd_even = mod(c,2);

    if odd_even == 1 %column is odd, supply indicator
        for r = 1:s(1,1);
            nICI(r,c) = (ICI(r,c)-min(ICI(:,c)))/(max(ICI(:,c))-
min(ICI(:,c)));
        end

    else %column is even, demand indicator
        for r=1:s(1,1)
            nICI(r,c) = (max(ICI(:,c))-ICI(r,c))/(max(ICI(:,c))-
min(ICI(:,c)));
        end
    end
end

%Factor Analysis
final_corr = corr(nICI);
[eigenvectors, eigenvalues] = eig(final_corr);

%Horn's Curve, N=46,p=10
[curvepoints] = Hornscurve(46,20);
figure
plot(curvepoints);hold on
B = sort(diag(eigenvalues),'descend'); %Scree plot of eigenvalues
plot(B,':ro') xlabel('Component #') ylabel('Eigenvalue')

%Calculate loadings
v1 = eigenvalues(1,1);e1 = eigenvectors(:,1);L1 = sqrt(v1)*e1;var1 = v1/20;
v2 = eigenvalues(2,2);e2 = eigenvectors(:,2);L2 = sqrt(v2)*e2;var2 = v2/20;
v3 = eigenvalues(3,3);e3 = eigenvectors(:,3);L3 = sqrt(v3)*e3;var3 = v3/20;
v4 = eigenvalues(4,4);e4 = eigenvectors(:,4);L4 = sqrt(v4)*e4;var4 = v4/20;
Total_Variance_Explained = (var1+var2+var3+var4)*100
L = [L1 L2 L3 L4];
%Unrotated eigenvalues, and communalities
%Communalities
for n = 1:20
```

```

        h(n) = L(n,1)^2+L(n,2)^2+L(n,3)^2+L(n,4)^2;
    end
h_2 = h';

%Eigenvalues
eig_1=sum(L1(:).^2);
eig_2=sum(L2(:).^2);
eig_3=sum(L3(:).^2);
eig_4=sum(L4(:).^2);
Sum = eig_1+eig_2+eig_3+eig_4;

%Kaiser's IFS
Unrotated_IFS = IFS2(L)

%Varimax Rotation
%Rotated Loadings
B = rotatefactors(L);

%Communlaties
for n = 1:20
    rh(n) = B(n,1)^2+B(n,2)^2+B(n,3)^2+B(n,4)^2;
end
rh_2 = rh';

%Eigenvalues
reig_1=sum(B(:,1).^2);
reig_2=sum(B(:,2).^2);
reig_3=sum(B(:,3).^2);
reig_4=sum(B(:,4).^2);
Sum = reig_1+reig_2+reig_3+reig_4;

%Kaiser's IFS
Rotated_IFS = IFS2(B)

%Calculating individual variable weights with squared factor loadings
for p = 1:4
    for n = 1:20
        sfl(n,p) = B(n,p)^2/Rotated_eigenvalues(p);
    end
end

eigen_var = [reig_1/Sum reig_2/Sum reig_3/Sum reig_4/Sum];
for i = 1:20
    [M,I] = max(sfl(i,:));
    intermed_1(i,1) = M;
    intermed_1(i,2) = eigen_var(I);
end
intermed_1;
intermed_2 = intermed_1(:,1).*intermed_1(:,2);
for i = 1:20
    weights(i) = intermed_2(i)/sum(intermed_2(:));
end
weights

```

```

%Calculating factor scores
scores = zscore(nICI)*inv(final_corr)*B;

%Reserving sign of factors 2 and 3
facilities = scores(:,1);
paves_dorms = -1*scores(:,2);
utilities = -1*scores(:,3);
nat_infra = scores(:,4);

%Weights of factors
for n = 1:4
    w(n) = Rotated_eigenvalues(n)/Sum;
end

%Calculating composite score with weighted factor scores
for i = 1:46
    ICC(i) =
w(1)*facilities(i)+w(2)*paves_dorms(i)+w(3)*utilities(i)+w(4)*nat_infra(i);
end
ICC=ICC';

T = table(facilities, paves_dorms, utilities, nat_infra, ICC, 'RowNames',txt);
T = sortrows(T, 'ICC', 'descend')
writetable(T, 'installation_ucc.txt');

```

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Vita

Captain Perry Cansick graduated from Wilson High School in West Lawn, Pennsylvania. He attended the University of Pittsburgh in Pittsburgh, Pennsylvania and earned a Bachelor of Science degree in Mechanical Engineering in April 2011. He commissioned through Detachment 730 AFROTC and was assigned to 375th Civil Engineer Squadron, Scott Air Force Base, Illinois. During his time at Scott AFB, Capt Cansick served as a project programmer and project manager. From December 2013 to June 2014, he deployed to the 376th Expeditionary Civil Engineer Squadron, Transit Center at Manas, Kyrgyzstan. In August 2014, he entered the Air Force Institute of Technology at Wright-Patterson Air Force Base, Ohio and earned a Master of Science degree in Engineering Management with a focus in infrastructure asset management. Upon graduation, he will be assigned to the 355th Civil Engineer Squadron, Davis-Monthan Air Force Base, Arizona.

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14. ABSTRACT Per the Air Force Strategic Master Plan, the Air Force will adjust their current basing structure to provide the most effective and efficient installations to support national defense objectives. The Air Force may be required to make strategic basing decisions that close installations and relocate missions to achieve an optimal basing structure. However, before making these decisions, the Air Force needs to have a comprehensive understanding of installation capacity. This research provides an operational definition of installation capacity, which is necessary for measuring installation-level, infrastructure capacity. Using this definition, the research evaluates a set of capacity indicators using principal component analysis (PCA) and exploratory factor analysis (EFA). The results identify the underlying structure of the capacity data and determine what factors influence capacity. In addition, the component and factor scores provide information about capacity characteristics at each installation, and how they compare to other installations. Finally, this research created a composite scoring model, the Installation Composite Capacity (ICC), which measures the overall capacity at each installation. The Air Force can use the results and insight gained from this research to develop an optimized basing structure that meets present, and future, defense needs.						
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